

From Human Annotation to LLMs: SILICON Annotation Workflow for Management Research

Xiang Cheng

Robert H. Smith School of Business, University of Maryland
xccheng@umd.edu

Raveesh Mayya, João Sedoc

Leonard N. Stern School of Business, New York University
{raveesh, js11531}@stern.nyu.edu

ABSTRACT

Unstructured text data annotation and analysis are fundamental to management research, often relying on human annotators through crowdsourcing platforms. While Large Language Models (LLMs) promise to provide a cost-effective and efficient alternative to human annotation, there lacks a systematic workflow that evaluate when LLMs are suitable or how to proceed with LLM-based text annotation in a reproducible manner. This paper addresses this methodological gap by introducing the “SILICON” (**S**ystematic **I**nference with **L**LMs for **I**nformation **C**lassification and **N**otation) workflow. The workflow integrates established principles of human annotation with systematic prompt optimization and model selection, addressing challenges such as developing robust annotation guidelines, establishing high-quality human baselines, optimizing prompts, and ensuring reproducibility across LLMs. We validate the SILICON workflow through seven case studies covering common management research tasks, including business proposal evaluation, dialog intent and breakdown analysis, review attribute detection. Our findings highlight the importance of validating annotation guideline agreement, the superiority of expert-developed human baselines over crowdsourced ones, the iterative nature of prompt optimization, and the necessity of testing multiple LLMs. Notably, we propose a regression-based methodology to empirically compare LLM outputs across prompts and models. Our workflow advances management research by establishing reproducible processes for LLM-based annotation that maintain scientific rigor. We provide practical guidance for researchers to effectively navigate the evolving landscape of generative AI tools effectively while maintaining transparency and reproducibility.

Key words: Large Language Models, Text Annotation, Workflow, Management Research

JEL Codes: C81, D83, O33, L86

* We thank Erich Battistin for his insightful suggestions on the statistical comparison of LLM outputs. We are also grateful to the authors who generously shared their annotation guidelines, human annotation samples, and raw data. Additionally, we extend our thanks to Aryaman Bansal, Julia Chen, Eric Chen, Jo-Lynn Kok, Annika Ma, Yilun Ma, Anantesh Mohapatra, Saumya Poddar, Aparna Vagvala, and Emily Yang for their valuable assistance in the development of annotation guidelines and baselines.

1. Introduction

The annotation of unstructured text data, using either crowdsourcing or natural language processing (NLP) tools, is an integral part of various social science disciplines, including psychology (Jackson et al. 2022), political science (Wilkerson and Casas 2017), and management research (Ghose and Ipeirotis 2011, Humphreys and Wang 2018). In management research specifically, machine learning and NLP have been widely employed to extract insights from unstructured text data, helping explain underlying mechanisms (Mayya et al. 2021). These applications range from sentiment and emotional content analysis (Liu et al. 2019, Chakraborty et al. 2022, Oh et al. 2023, Melumad et al. 2019, Yang et al. 2019) to product attribute classification (Bronnenberg et al. 2024, Kwark et al. 2021, Banerjee et al. 2021), advertisement analysis (Lee et al. 2018, Shi et al. 2022), managerial response analysis (Deng and Ravichandran 2023), consumer review analysis (Liu et al. 2019, Mayya et al. 2021, Hong et al. 2021, Lee et al. 2023a), and product categorization (Lee and Hosanagar 2021).

A critical component of annotating unstructured text data involves human subjects generating appropriate *labels* for machine usage. In the past, researchers have relied on undergraduate research assistants (RAs) from their universities for annotation tasks. The past decade has seen an increased adoption of crowdsourcing platforms such as Amazon Mechanical Turk or Prolific for data collection, surveys, and annotation tasks that inform NLP models for sentiment analysis, binary classification, and multi-label classification (e.g., Lee and Hosanagar 2021, Hong et al. 2021). These platforms provide access to a diverse participant pool, rapid data collection and cost-effectiveness compared to local RAs, thereby enhancing research feasibility, generalizability, and external validity (Aguinis et al. 2021, Goodman and Paolacci 2017).

Large Language Models (LLMs), a class of Generative Artificial Intelligence (GenAI) tools, promise to revolutionize text data annotation. Commercial API-based models such as GPT-4o and Claude 3.5 Sonnet, as well as open-source models such as LLaMA 3.1, demonstrate remarkable natural language generation capabilities. Trained on large amounts of human-generated text, these

tools can generate notably human-like text responses, to a point where distinguishing between human and machine outputs has become challenging (Boussioux et al. 2023, Dillion et al. 2024).

Given their potential advantages in time-efficiency and cost-effectiveness over crowdsourcing platforms, researchers are increasingly employing LLMs for text annotation tasks (Pangakis et al. 2023, Zhang et al. 2024, Yeverechahu et al. 2024). For instance, GenAI has demonstrated superior cost-effectiveness over crowdsourcing platforms for tasks like stance detection (Gilardi et al. 2023). Alarmingly, emerging investigations have shown that some purportedly human responses from crowdsourcing platforms may actually be LLM-generated, undermining the reliability of “human-generated” data (e.g., Veselovsky et al. 2023).

Despite the growing adoption of LLMs for text annotation tasks (Rathje et al. 2024, Carlson and Burbano 2024), there is a notable gap in the literature regarding a unified, well-justified methodology for guiding this process. While existing research emphasizes validating LLM performance against human labels (Pangakis et al. 2023) or provides general guidelines for such (e.g., Törnberg 2024), these approaches lack detailed, step-by-step instructions for the entire process with proper justifications. Additionally, some studies focus on benchmarking LLM performance across various scenarios; however, the results often become obsolete quickly due to the rapid advancements in LLMs (Gilardi et al. 2023). What researchers need instead is a standardized, reproducible¹ process that remains relevant regardless of model improvements. This process should bridge established principles of human annotation—emphasizing validity, transparency, and reproducibility (Hovy and Lavid 2010)—with unique aspects of LLM implementation, including systematic prompt optimization and model selection. Figure 1 visualizes the sequential challenges researchers face when implementing LLMs for text annotation tasks, progressing from establishing annotation guidelines and human baselines to selecting appropriate prompts and models. A critical consideration throughout this process is ensuring reproducibility of annotation results, regardless of the LLM employed. To the best of our knowledge, no existing study provides a systematic workflow that addresses these questions comprehensively with rigorous validation and justification.

¹We are interested in understanding reproducibility not only in the “same model, same prompt” scenario, but also in the “different models, same prompt” scenario. The first scenario is straightforward as long as researchers faithfully report the versions of the models used, the prompt, and the hyperparameters of the LLMs (e.g., temperature, top-p). The second scenario is less straightforward and is therefore the focus of this study.

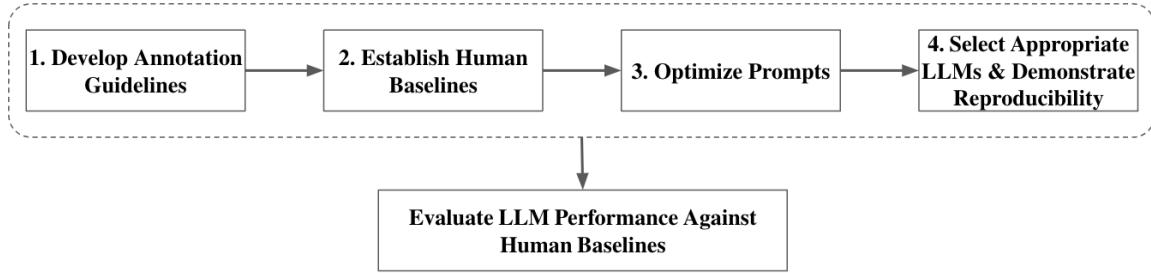


Figure 1 The “How to” process of using LLMs for text annotations

Our proposed SILICON workflow (S_ystematic I_nference with LLMs for I_nformation Classification and N_otation) addresses this gap in management literature by providing a step-by-step guide for leveraging LLMs for text annotation. Our workflow emphasizes a standardized approach for developing annotation guidelines and human baselines, and incorporates an iterative process for prompt optimization and model selection, ensuring transparency and reproducibility throughout the annotation process.

To validate the efficacy of our workflow, we evaluated the performance of several state-of-the-art LLMs (including GPT-4 Turbo, GPT-4o, Claude 3.5 Sonnet, Gemini 1.5 Pro, and open-source LLaMA 3.1 70B) against the established human annotation methodology on commonly encountered tasks in management research. These tasks included business proposal evaluation (Obermeier and Mayya 2024), review categorization (Liu et al. 2019), intent classification and breakdown analysis from customer support dialogs, language toxicity detection (Saha et al. 2023), and sentiment analysis (Sen et al. 2020), among others.

We outline the following solutions and recommendations in response to the identified challenges: *For question (1)* (how to develop annotation guidelines), we demonstrate that developing *prescriptive annotation guidelines* requires an iterative process and is not one-shot as researchers often do. While established protocols for creating annotation guidelines exist, we caution against directly adopting pre-existing guidelines and annotation baselines from other papers without careful evaluation. *For question (2)* (how to establish the human baseline for LLM evaluation), we argue that researchers should first verify high level of agreement among human annotators regarding the annotation guidelines before proceeding. Th evaluation process requires comparing LLM performance

against high-quality human annotation baseline, preferably established by domain experts or RAs rather than crowdsourced workers. *For question (3)* (how to optimize prompts and demonstrate the reproducibility of LLM results), we emphasize maintaining fairness in LLM-human comparisons by preserving the exact content of annotation guidelines in LLM prompts. Optimization efforts should focus on the “meta prompt”, —all elements except annotation guidelines content. *For question (4)* (how to select appropriate LLM models), we emphasize the importance of testing multiple models against the ground truth. Furthermore, once researchers decide on a single model to implement for a large-scale dataset, they should demonstrate that the results derived from LLM annotations remain consistent even if they were to choose another model with reasonably similar performance. Such a demonstration helps researchers argue for the reproducibility of the annotation results, i.e., their findings do not depend on a specific model. We propose that one way to demonstrate such reproducibility is to statistically compare the performance across multiple LLMs and identify whether a set of models produces statistically indistinguishable results.² To achieve this goal, we provide a regression-based methodology to empirically compare results across various models.

Our paper advances the methodological frontier in management research by introducing a systematic workflow for integrating LLMs in text analysis tasks. Unlike existing approaches that focus solely on performance benchmarks, we develop a systematic workflow that remains robust even as LLM capabilities evolve. The SILICON workflow provides management researchers with actionable guidance across the entire annotation process—from developing rigorous annotation guidelines, crafting effective meta prompts, selecting appropriate model to establishing reproducible metrics. Through extensive case studies, we highlight several important findings. We demonstrate that clear, expert-validated annotation guidelines are essential for reliable analysis, and baselines crafted by experts uphold significantly higher standards compared to those developed by crowdsourced workers. Additionally, we emphasize the importance of optimizing prompts using fixed guidelines and

²The most rigorous approach to demonstrate reproducibility would involve applying multiple models to annotate the entire dataset and verifying whether the analysis results remain consistent across annotations from different models. However, this approach is often infeasible due to budget constraints. Therefore, we adopted a regression-based methodology to address this issue from a statistical inference perspective.

refining “meta-prompts” through techniques like persona settings and chain-of-thought prompting. We also demonstrate the varied performance of LLMs across different tasks and stress the need to test multiple LLMs. To ensure reproducibility, we use a regression-based method that validates annotation results across alternative LLMs. Together, these insights provide researchers with a comprehensive, adaptable framework to leverage LLMs effectively while maintaining methodological rigor and reproducibility in management research.

2. Conceptual Background and Related Literature

2.1. Science of Annotation: Prescriptive Annotation Process and Reproducibility

The effectiveness of text annotation processes fundamentally depends on establishing consistent interpretation across annotators. Many annotation tasks face challenges due to annotator perspectives influenced by their socio-economic backgrounds (Basile et al. 2021). For example, toxicity detection labels can vary significantly based on annotators’ racial identities (Sap et al. 2019). Researchers have addressed this inherent subjectivity in annotation processes by choosing between *descriptive* approaches that capture diverse perspectives or *prescriptive* approaches that enforce consistent interpretation (Rottger et al. 2022). While neither approach is inherently superior, prescriptive approaches are particularly valuable in management research where the goal is often to extract information aligned with precise, unified definitions of concepts.

The development of prescriptive annotation guidelines, however, is an iterative process rather than a one-time task. For instance, the LEAP process (Lee et al. 2023b) emphasizes that both guidelines and ground truth evolve through continuous refinement until annotators achieve substantial agreement on the intended interpretation. This iterative process involves documented discussions between guideline creators and annotators, systematic revision of guidelines based on these discussions, and validation through agreement metrics on sample annotations. Such systematic documentation of the guideline development process ensures that the final annotations reflect the researchers’ intended construct rather than individual annotator biases, while being completely reproducible.

Relatedly, reproducibility in annotation processes extends beyond mere reliability or inter-annotator agreement (Artstein 2017). True reproducibility requires that independent researchers can obtain consistent results using the same methodology (Fišar et al. 2024). This necessitates complete transparency in the annotation process, from initial guideline development through final labeling. The LEAP process, for instance, specifically advocates for recording discussions and maintaining detailed transcripts to facilitate cross-paper analysis and ensure full reproducibility (Lee et al. 2023b).

While these principles are well-established for human annotation processes, their application to LLM-based annotation introduces new challenges. Beyond traditional annotation guidelines, LLM implementation requires carefully crafted “meta” system prompts that help models understand tasks and return results in structured usable formats. Currently, no workflow exists that adapts these established principles of reproducibility to the unique requirements of LLM-based annotation, creating a gap in the literature that our work aims to address.

2.2. LLMs for Text Annotation

Given that LLMs are trained on vast volumes of human-generated text, researchers have naturally explored their capacity to replicate human judgment across various domains. Recent applications span using LLMs as an agent or subject (Manning et al. 2024, Xie et al. 2024, Doshi et al. 2024), stance detection (Gilardi et al. 2023), and policy interpretation (Leek et al. 2024), with researchers leveraging LLMs’ apparent ability to understand and categorize text in ways that mirror human cognition.

However, this assumed equivalence between LLM and human judgment faces important theoretical and practical challenges. The Polanyi’s paradox suggests that humans express in language only a fraction of their inherent understanding, making it potentially problematic to assume that models trained solely on expressed language can fully capture human judgment (Autor 2014). Recent empirical work supports this concern, with studies indicating that LLMs are not yet ready to systematically replace human judges in natural language processing tasks (Bavaresco et al. 2024).

Nevertheless, rather than requiring LLMs to replicate the full complexity of human cognition, management scholars often need models to reliably apply specific, well-defined annotation criteria at scale. This distinction is crucial—the goal shifts from mimicking human thought processes to achieving consistent agreement with human annotators on clearly defined tasks. However, establishing such agreement requires a systematic process that first documents human annotators' explicit reasoning and then verifies whether LLMs can reliably apply the same logic.

LLM annotation results depend on multiple factors, including prompts, model selection, and annotation guidelines (Törnberg 2024). Current research lacks a comprehensive evaluation of how these factors play out across different types of management research tasks, which this paper intends to quantify.

3. The Proposed Workflow: SILICON

The SILICON workflow addresses the methodological challenges of utilizing LLMs for text annotation in management research through a systematic, reproducible approach. SILICON particularly emphasizes three critical aspects: (1) the development of prescriptive annotation guidelines that can be consistently interpreted by both humans and LLMs, (2) the establishment of robust human baselines against which LLM performance can be evaluated, and (3) a systematic approach to prompt optimization and model selection that ensures reproducibility across different LLM implementations. Figure 2 illustrates our proposed workflow.

3.1. Creation of Annotation Guidelines and Human Baseline

3.1.1. Creating annotation guidelines. The annotation process begins with researchers defining specific objectives of the tasks and core concepts to measure or extract. These objectives form the foundation for all subsequent methodological decisions.

As a next step, researchers investigate whether well-defined guidelines already exist in the literature. While leveraging existing guidelines can be efficient, their mere existence does not guarantee their suitability. As demonstrated in the results (section 5.1.1), directly adopting existing guidelines without proper validation could lead to poor inter-annotator agreement, ultimately compromising

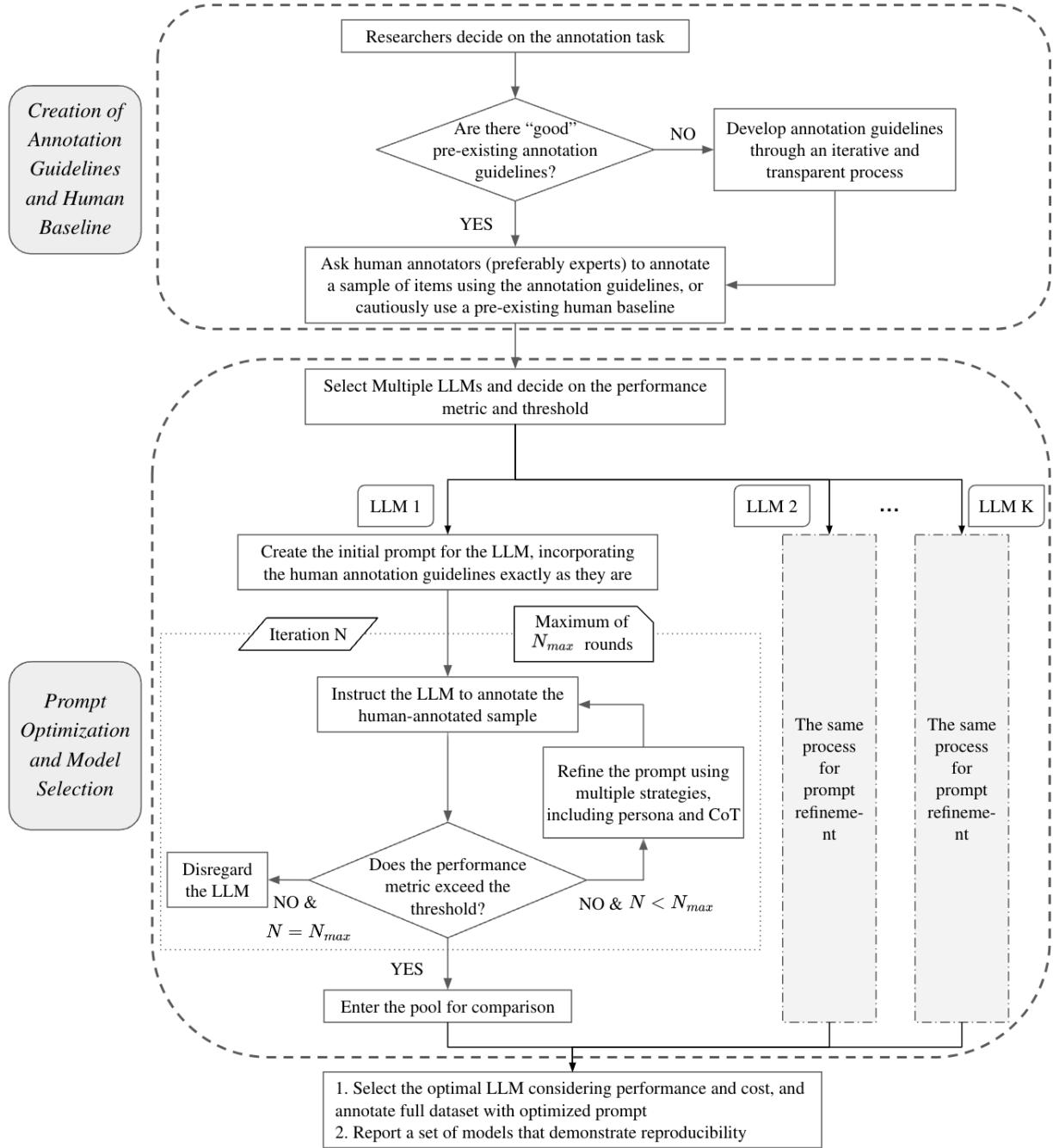


Figure 2 SILICON: A Systematic Framework for LLM-based Text Annotation

both human annotation quality and LLM utilization effectiveness. In cases where existing guidelines prove suitable after validation, it is efficient to adopt them.³ The SILICON workflow builds on

³ In most research scenarios, however, researchers encounter a lack of adequate guidelines, require them to develop new guidelines through an iterative and transparent process.

established practices in NLP literature (for instance, see Lee et al. 2023b) to provide a systematic protocol for guideline development.

The SILICON process begins with researchers drafting preliminary definitions of key concepts and objectives, which are provided to a team of RAs for independent annotation of an initial sample. The structured refinement cycle is defined as follows:

Iterative Annotation Process

1. RAs independently annotate a sample dataset
2. Measure inter-annotator agreement (IAA) and compare it with the predefined threshold
3. If IAA threshold is not met:
 - Conduct documented discussions focusing on disagreements
 - Reshuffle and re-annotate the *same* sample independently
 - Repeat until threshold is met
4. Once threshold is met, proceed to annotate a *new* sample
5. Process concludes when RAs achieve the threshold on first pass with a new sample

The process then moves to documentation, where RAs independently draft annotation guidelines based on their collective experience.⁴ The team reconvenes to collaboratively merge these drafts. This systematic approach ensures that the resulting guidelines are both precise and reproducible, having emerged from a documented process of iterative refinement with consensus-building.

3.1.2. Creating human annotation baseline. The establishment of robust human annotation baseline serves as a critical reference point for evaluating LLM performance in annotation tasks. This baseline serves as the reference standard against which LLM annotations are compared, ultimately determining whether LLMs are suitable for the intended task. A critical question in this process is who should develop the human annotation baseline. In other words, the development of annotation baseline needs researchers to carefully consider three key elements: *annotator expertise*, *baseline reliability* and *sample adequacy*.

⁴ All meeting recordings and transcripts are provided to the RAs.

Annotator Expertise: Human annotation baselines typically fall into two categories: expert-generated baselines and crowdsourced workers-generated baselines. Expert-generated baselines are produced by individuals with substantial domain knowledge and a thorough understanding of the annotation guidelines. These experts might include researchers or trained RAs who participated in iteratively developing the annotation guidelines. In contrast, crowdsourced baselines, while accessible and cost-effective, are created by workers from platforms like Amazon Mechanical Turk, who may lack the domain-specific knowledge. Although some studies have evaluated LLM performance against crowdsourced baselines (Pangakis et al. 2023), we advocate for expert-generated baselines for a more rigorous evaluation, as we demonstrate in Section 5.1.3.

Baseline Reliability: Baseline reliability hinges on demonstrably high inter-annotator agreement. The underlying assumption that human annotations represent ground truth is valid only when annotators achieve consistent agreement in their labeling decisions. This is particularly critical when using pre-existing baselines from published literature, where researchers must verify the IAA within the baseline sample before adoption. Misaligned or poorly validated baselines can fundamentally compromise the evaluations of LLM performance.

Sample Adequacy: Sample size requirements for the baseline must balance statistical rigor with practical constraints. The baseline dataset should be large enough to support robust statistical inferences about agreement rates and adequately represent all task labels. Sample size calculations should factor in task complexity, label diversity, and expected variability in annotation agreement. Using statistical formulas that consider confidence levels and margins of error can help determine the minimum required sample size.⁵ In our case studies, we found that baseline sample sizes of 120–200 items typically provided sufficient statistical power while remaining practically manageable.

3.2. LLM Performance Evaluation, Prompt Optimization, and Model Selection

3.2.1. Choice of performance metric. The evaluation of LLM performance against the human baseline requires careful selection of an appropriate performance metric that can effectively

⁵ For instance, achieving a 95% confidence level with a small margin of error may necessitate a larger sample.

measure annotation agreement. Preferably, this metric must serve dual purposes: quantifying the agreement between human and LLM annotations, and measuring inter-annotator agreement (IAA) during guideline development and baseline establishment.

Several established metrics exist for evaluating IAA, such as Cohen’s Kappa, Fleiss’ Kappa, and Krippendorff’s Alpha. As a general rule, researchers are encouraged to select a performance metric that best suits the specific annotation task characteristics and provide clear justification for their choice, as no universal solution exists.

In our study, we consistently employ Cohen’s Kappa as the performance metric. Cohen’s Kappa measures the level of agreement between two annotators while adjusting for chance agreement (Cohen 1968), and is given by: $\kappa = \frac{P_o - P_e}{1 - P_e}$, where P_o represents the relative observed agreement among raters, and P_e denotes the hypothetical probability of agreement by chance.

Our adoption of Cohen’s Kappa is grounded in three key reasons. First, it is inherently designed for pairwise agreement analysis, which aligns well with our objective of comparing a single LLM against the human baseline. In this context, we treat the LLM as one “annotator” and compare its annotations against the human consensus (also considered the “ground truth”).⁶ Second, Cohen’s Kappa metric demonstrates scalability, extending naturally to scenarios involving multiple annotators through calculation and averaging of pairwise Kappa scores. This characteristic proves particularly valuable during the initial stages of the SILICON process—in developing annotation guidelines and establishing the human baseline—where evaluation typically involves more than two human annotators. Third, Cohen’s Kappa can be adapted effectively to multi-label classification tasks, where items may belong to multiple categories simultaneously. By incorporating context-dependent weighting matrices during the calculation, the metric enables a careful assessment of agreement across complex tasks. We provide detailed specifications of this adaptation in Appendix A.

⁶ Human consensus or the “ground truth” is obtained by aggregating multiple human annotators’ results through methods such as majority voting.

3.2.2. Prompt optimization. Prompt optimization plays a critical role in maximizing LLM performance due to their unique nature and operational requirements. Unlike human annotators who can interpret contextual nuances, LLMs rely on explicit and detailed instructions to generate outputs that are accurate, contextually appropriate, and aligned with task objectives. While extensive research and industry guidance exists on prompt optimization⁷, we emphasize the importance of maintaining a clear distinction between text annotation process and what we term the *meta prompt*—all additional instructional elements of the prompt that guide LLM’s behavior.

To ensure fair comparisons between LLMs and human annotators, annotation guidelines must be included verbatim within the prompts. However, researchers can optimize several other aspects of the prompt structure to optimize performance. Specifically, our paper focuses on three key areas of *meta prompt*: the placement of annotation guidelines, the adoption of task-specific personas, and the inclusion of reasoning strategies such as the chain-of-thought method.

The placement of annotation guidelines: The positioning of annotation guidelines within the prompt structure can significantly influence annotation quality. Most LLMs distinguish between a *system* role and a *user* role. The system role governs the overall behavior patterns of the model, while the user role conveys task-specific instructions. Empirical evidence from our case studies suggests that embedding annotation guidelines within the system role often yields superior results, as this approach leverages the overarching influence of the system prompt over the model’s output strategy. Figure 3 illustrates the different positions of annotation guidelines using the OpenAI Chat Completion Playground⁸. The image to the left retains the default system message with the entire annotation guidelines placed in the user role. The image to the right places the annotation guidelines in the system role with only the input content and formatting requirements placed in the user role.

The adoption of task-specific personas: Another factor in optimizing meta prompts is the definition of personas (Hu and Collier 2024), which refers to the specific role that the LLM assumes

⁷ For instance, Anthropic: <https://docs.anthropic.com/en/docs/build-with-claude/prompt-engineering/overview>

⁸ <https://platform.openai.com/playground/chat?models=gpt-4o>

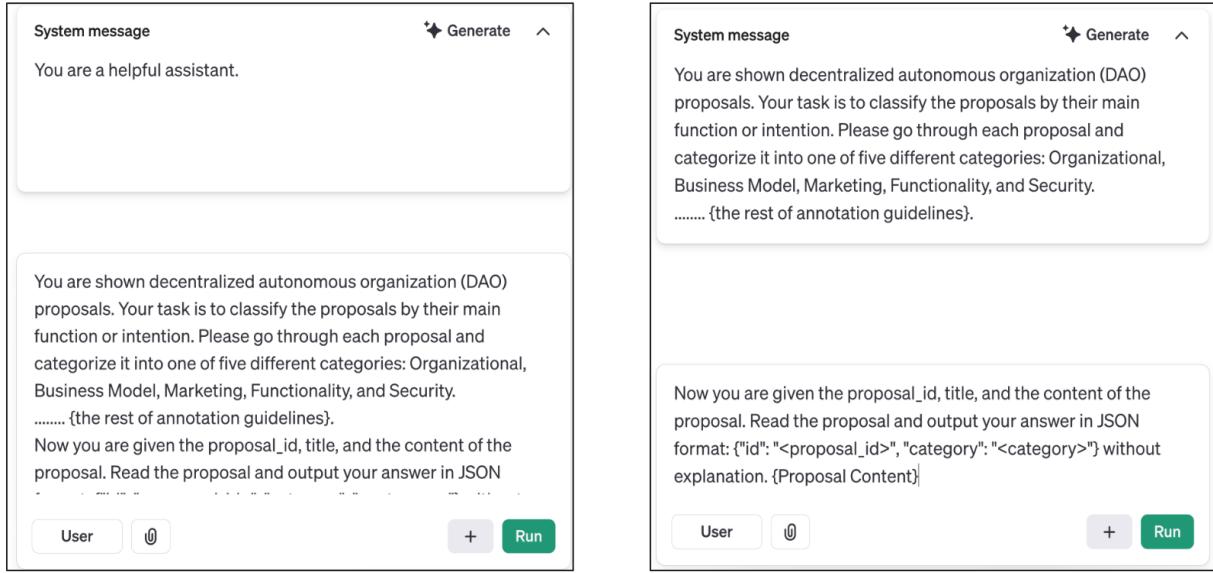


Figure 3 Illustration of Different Positions of Annotation Guidelines in the Prompt

during the annotation process (for example, “You are a business analyst evaluating business proposals.”) By clearly specifying the role, researchers can align model’s perspective with the required domain-specific knowledge. Given that some annotation guidelines already contain sufficient background information and domain framing, additional persona setting may be redundant.

The inclusion of reasoning strategies: Incorporating structured reasoning strategies, such as the chain-of-thought (CoT) method (Wei et al. 2023), serves as the third key optimization approach. By instructing the model to articulate its inferencing process step by step, researchers can improve performance on tasks requiring complex reasoning or multi-step problem-solving. For example, directing the model to “Read the proposal, briefly explain your labeling logic, and then output your answer” has been shown to enhance output clarity and accuracy.

Additionally, from the practical implementation standpoint, researchers should consider two additional factors. First, requiring LLMs to provide answers in JSON format ensures consistent, structured output. Second, setting a maximum number of optimization iteration helps maintain efficiency. If the LLM fails to meet the performance threshold after these iterations, researchers should consider selecting a different LLM or acknowledging the limitations of LLMs for the given annotation task.

3.2.3. A regression-based approach for LLM performance comparison. On a more rigorous perspective of comparing annotation performance—whether across different LLM models or different prompts—we recommend the strategies outlined below. We propose a regression-based approach for identifying treatments (models or prompts) that yield statistically equivalent performance. Specifically, we treat each model or prompt as a distinct “treatment” and use item–treatment-level annotations as our unit of analysis (where “item” refers to a single data unit such as a tweet or business proposal). In this setting, when annotating N business proposals using K different treatments, the resulting dataset has $N \cdot K$ observations. Our main dependent variable is the agreement between the focal treatment’s annotation and the human-provided ground truth—coded as 1 if they match and 0 otherwise. We then regress these agreement outcomes on $(K - 1)$ binary treatment indicators (with one treatment omitted as the baseline), clustering the standard errors at the item level to account for the repeated-measures structure. Technical details of this regression are provided in Appendix B.

Researchers can use F-statistics, Wald tests, and confidence intervals to determine which treatments produce overlapping or significantly different results from the baseline. As illustrated in Section 5.3.3, these tests can be visualized through coefficient plots to help interpret performance differences. Further, while our working example focuses on accuracy as the agreement metric, the same approach can adapt Cohen’s Kappa or other metrics, acknowledging a small discrepancy in how item-level vs. aggregate chance-correction is handled. By systematically comparing multiple models or prompts in a single framework—and clustering standard errors to address item-level correlation—researchers can confidently identify which treatments yield statistically equivalent annotations and which treatments are significantly better or worse than the baseline treatment.

3.2.4. Model selection and identifying statistically equivalent LLMs. The final phase of implementing LLM based annotation involves systematic evaluation and selection of appropriate LLM model. This comparison serves two critical purposes: identifying the most effective model for a specific task and establishing reproducibility through statistical equivalence among multiple models.

First, as shown in Section 5.3.2, the relative performance rankings of models can vary significantly across tasks. This variability underscores the importance of task-specific evaluations, as no single model universally outperforms others. Second, it is also important for researchers to demonstrate the reproducibility of annotation results produced by LLMs. This involves identifying a subset of models that can produce statistically equivalent results for a focal task. This again requires the use of the regression-based approach. Since the samples for human annotations are randomly chosen, this regression approach allows researchers to argue that results generated by focal LLM on a large scale will have the same order of performance accuracy as compared to other models of comparable quality. This comprehensive approach strengthens the validity of large-scale LLM annotation implementations and supports the broader adoption of LLM-based annotation in management research.

4. Evaluation

4.1. Case Study Scenarios

To rigorously evaluate the SILICON workflow across various management research contexts, we conducted detailed analysis of seven representative scenarios in management research. Our evaluation strategy divided these scenarios into two distinct categories based on the depth and control of the validation process. The first category comprised four scenarios—business proposal evaluation, review attribute detection, dialog intent classification and breakdown analysis, and geographical information extraction. These scenarios were extensively examined through the development of annotation guidelines and the establishment of expert-validated human baselines, achieved by recruiting three RAs for each task. The second category comprised three supplementary scenarios—language toxicity detection, criticism stance detection, and sentiment analysis. For this category, we relied on the published papers' annotation guidelines and human baselines as external datasets. However, these scenarios present certain limitations for our analysis. For instance, we were unable to verify the inter-annotator agreement for the human baselines due to a lack of access to the necessary data in the published datasets. Additionally, these baselines are likely derived

from crowdsourced baselines rather than expert baselines, likely exposing the lower bound of the effectiveness of LLMs. Consequently, these three scenarios are treated as supplementary evidence, while our main conclusions are drawn exclusively from the first four scenarios. In the following sections, we provide detailed examination of specific text annotation scenario, their relevance to management research, and our methodological approach to implementation.

4.1.1. Business proposal evaluation. Business documentation analysis, particularly of proposals, crowdfunding initiatives, and corporate statements, plays a critical role in conveying business-related information and is essential for analyzing organizational decision making and strategic behavior (Cao et al. 2019). Our first case study focuses on the classification of decentralized autonomous organization (DAO) business proposals, building on the work of Obermeier and Mayya (2024). This classification task requires DAO proposals based on their primary function or intention. Specifically, each proposal was categorized into one of six categories: Organizational, Business Model, Marketing, Functionality, Security, or Other. The categorization process aims to reveal patterns in how DAOs delegate and structure decision rights across their platforms. We developed our annotation guidelines through the iterative SILICON process described in Section 3.1.1, using the original paper's guidelines as an initial instructions for RAs. The prompt, including both the annotation guidelines and the meta prompt, appears in Appendix D.1.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Understanding DAO governance through systematic analysis of business proposal content and decision delegation patterns	Manual classification by RAs into six predefined categories	Developed expert-validated guidelines with 3 RAs; established baseline using 121 proposals; tested multiple LLM configurations	1. High-performing LLMs achieved moderate to high agreement with expert baseline 2. Crowdsourced workers' annotations were only as good as the median-performing LLMs

4.1.2. Review attribute detection. Online reviews contain critical information that help the understanding of consumer purchase decisions. We build on the work of Liu et al. (2019),

where authors used a large scale deep learning approach to identify the presence of six attribute in the product reviews, including price, performance feature, relatability/durability, conformance, aesthetics, and perceived quality. This is a multi-label classification task which provides insights into how different product attributes influence consumer decision-making. Using the dataset from the original study, we implemented the SILICON framework to develop comprehensive annotation guidelines through our iterative process. The complete annotation protocol, including detailed guidelines and meta prompt specifications, is provided in Appendix D.2.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Quantifying consumers' purchasing decisions through systematic analysis of product review content	Training a deep learning model using 5,000 reviews annotated by Amazon Mechanical Turk workers	Developed expert-validated guidelines with 3 RAs; established baseline using 180 reviews; tested multiple LLM prompt and model configurations;	1. Moderate agreement achieved with expert baseline across selected models 2. Significant performance variation observed between different LLMs for this complex multi-label task

4.1.3. Dialog intent classification and breakdown analysis. Dialog analysis has been critical in various domains, particularly in understanding and improving human-computer interaction. We focus on two critical aspects of dialog analysis: dialog intent classification (Stolcke et al. 2000) and breakdown analysis (Higashinaka et al. 2016), using a sample of customer service dialog data obtained from a Hugging Face dataset⁹.

The first task, dialog intent classification, requires human annotators to classify the intention of each utterance into one or multiple categories (i.e., multi-label classification) including factual questions, yes/no questions, task commands, invalid commands, appreciations, complaints, comments, statement non-opinions, positive answers, and negative answers. The second task, the dialog breakdown analysis, focuses on identifying whether an utterance in the conversation leads to a breakdown, classifying each utterance as: (1) not a breakdown, (2) a possible breakdown, or (3)

⁹ <https://huggingface.co/datasets/bitext/Bitext-customer-support-llm-chatbot-training-dataset>

confirmed breakdown. TThe complete annotation protocol for both tasks is provided in Appendix D.3.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Evaluating human-computer interactions in customer support through systematic dialog analysis	None. This is a novel evaluation of human-computer interactions in customer support through systematic dialog analysis	Developed expert-validated guidelines with 3 RAs; established baseline using 195 conversational turns; tested multiple LLM prompt and model configurations	1. Intent classification showed consistently low agreement between LLMs and expert baseline 2. Breakdown analysis demonstrated moderate to high agreement levels across tested models

4.1.4. Geographical information extraction. The data in this case is derived from Shi et al. (2023), which consists of HTML files from Amazon product pages. The task involves analyzing each product’s HTML content to determine the presence of manufacturing information and, if present, identifying whether the product is manufactured within the United States or internationally. There are two subtasks: identifying location disclosure from seller-disclosed information, and identifying location disclosure from customer reviews. Such task is non-trivial, because manufacturing information may be conveyed in various ways, often requiring expert judgment to accurately categorize whether a product is manufactured domestically or abroad. The prompt for this task is shown in Appendix D.4.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Examining whether and how the disclosure of seller location affects the product sales and pricing strategies	Recruiting RAs to manually identify the geographical information disclosure through product webpages	Developed expert-validated guidelines with 3 RAs; established baseline using 200 product webpages; tested multiple LLM prompt and model configurations	GPT-4o achieved a moderate to high level of agreement level compared to expert baseline

4.1.5. Language toxicity detection. Detecting toxic content in textual data plays a critical role in management research, offering insights into a range of organizational and social dynamics. Toxic interactions, such as hate speech or fear-based messaging, can significantly impact online communities (Matook et al. 2022, Sibai et al. 2024), and organizational behavior (Rosette et al. 2013). For this task, we utilize the pre-existing annotation guidelines and the human baseline publicly available from Saha et al. (2023). The annotated items are social media posts from Gab. The task is to mark each post as a) fear speech, b) hate speech, c) normal, or d) both fear speech and hate speech (if the post contains elements of both). The detailed prompt is shown in Appendix D.5.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Demonstrating fear speech’s prevalence, influence, and subtlety compared to hate speech on social media platforms	Manual classification into one of four types using a combination of experts and Amazon Mechanical Turk workers	Used the annotation guidelines and a random sample of the human baseline from the original paper which involves 160 posts; explored multiple prompts and models	Agreement level between LLMs and crowdsourced baseline is moderate to low

4.1.6. Criticism stance detection. We selected this case because the core task—criticism stance detection—can be generalized to address a broad range of organizational and social challenges. Specifically, we use data from Peng et al. (2022), which focuses on detecting the criticism stance of tweets about certain academic papers, framing it as a binary classification task. The detailed prompt is shown in Appendix D.6.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Assessing online attention and criticism toward retracted scientific papers over time	Manual classification of Twitter posts to identify expressions of criticism toward specific scientific papers, using trained annotators	Used the annotation guidelines and a random sample of the human baseline from the original paper consisting of 180 posts; explored multiple prompts and models	Agreement level between LLMs and crowdsourced baseline is moderate

4.1.7. Sentiment analysis. Sentiment analysis plays a pivotal role in management research, with applications across various contexts such as social media platforms (Zhang et al. 2016, Oh et al. 2023), e-commerce platforms (Homburg et al. 2015), financial markets (Loughran and McDonald 2014, Antoniou et al. 2016), and firm-public communications (Choudhury et al. 2019). Sentiment analysis approaches, whether dictionary-based or machine learning-based, generally achieve high accuracy (Frankel et al. 2022). In this study, we assess whether text annotations generated by LLMs can produce similarly well-aligned results. For this task, we utilize annotation guidelines and the human baseline from Sen et al. (2020). The prompt is provided in Appendix D.7.

Research Context	Original Text Annotation Approach	SILICON Implementation	Key Findings
Comparing human and computational attention in text classification tasks, focusing on sentiment analysis	Manual labeling of sentiment value and human attention maps of Yelp customer reviews using Amazon Mechanical Turk workers	Used the annotation guidelines and a random sample of the human baseline from the original paper consisting of 120 reviews; explored multiple models	Agreement level between LLMs and crowdsourced baseline is very high across all models tested

4.2. Prompt and Model Specifics

To comprehensively evaluate performance, we tested multiple prompts and models for each task.¹⁰ The prompt strategies included a base prompt, a prompt with persona settings, and a prompt with chain-of-thought, all unified in their placement within the system role rather than the user role. These prompts were initially tested using GPT-4 Turbo to establish a benchmark. Based on the results from GPT-4 Turbo, we identified the optimal prompt by balancing performance and cost considerations¹¹. This optimal prompt was then applied across several models, including GPT-4o, Claude 3.5 Sonnet, Gemini 1.0 Pro, Gemini 1.5 Pro, LLaMA 3 70B, and LLaMA 3.1 70B.¹² This systematic approach allowed us to compare model performance effectively.

¹⁰ The geographical information extraction task was an exception to this approach. Due to the large size of the HTML input and budget constraints, this task was tested using only one prompt on GPT-4o.

¹¹ For example, while chain-of-thought often achieved the highest performance, the improvement was relatively small in some cases. Given the significant increase in token cost associated with chain-of-thought, we selected the second-best prompt for use with other models.

¹² More specifically, we used the following versions of models: gpt-4-1106-preview (for GPT-4 Turbo), gpt-4o-2024-08-06, claude-3-5-sonnet-20240620, gemini-1.0-pro, gemini-1.5-pro, Llama-3-70B-Instruct, and Llama-3.1-70B-Instruct.

Acknowledging that the best-performing prompt might vary between models, we further examined this variability. Specifically, we tested all three prompt strategies, altering their placement (system role versus user role) to generate six distinct prompts. These prompts were applied to a selective subset of four models, focusing particularly on the business proposal evaluation task to analyze differences in performance.

For consistency, the temperature setting was fixed at 1 across all models, aligning with the default value for GPT-4 Turbo. Detailed descriptions of the prompts for each task are provided in the appendix D.

5. Results

5.1. On the Creation of Annotation Guidelines and Human Baseline

We first present the results on the creation of annotation guidelines and the establishment of a human baseline. From four tasks—business proposal evaluation, dialog intention classification and breakdown analysis, review attribute detection, and geographical information extraction—we developed annotation guidelines using RAs. Our analysis of this guideline development and human baseline creation process reveals notable insights.

5.1.1. Caution the use of pre-existing annotation guidelines. For each task, during the initial sample annotation, we provided RAs with pre-existing annotation guidelines and instructed them to complete the annotation tasks independently. As shown in Figure 4, in the first iteration, three out of four tasks (excluding the geographical information extraction task) exhibited relatively low mean Cohen’s Kappa values—below 0.5—and for the dialog and review attribute tasks, values were as low as 0.2. These results suggest that relying solely on pre-existing annotation guidelines can be problematic, as they may fail to ensure consistent agreement among annotators. This poor agreement level compromises the reliability and effectiveness of the human baseline. However, this does not imply that pre-existing annotation guidelines should not be used. It is essential to validate their effectiveness by assessing agreement levels. For example, the geographical information extraction task achieved a high mean Cohen’s Kappa in the initial sample annotation, demonstrating the potential utility of well-designed pre-existing guidelines.

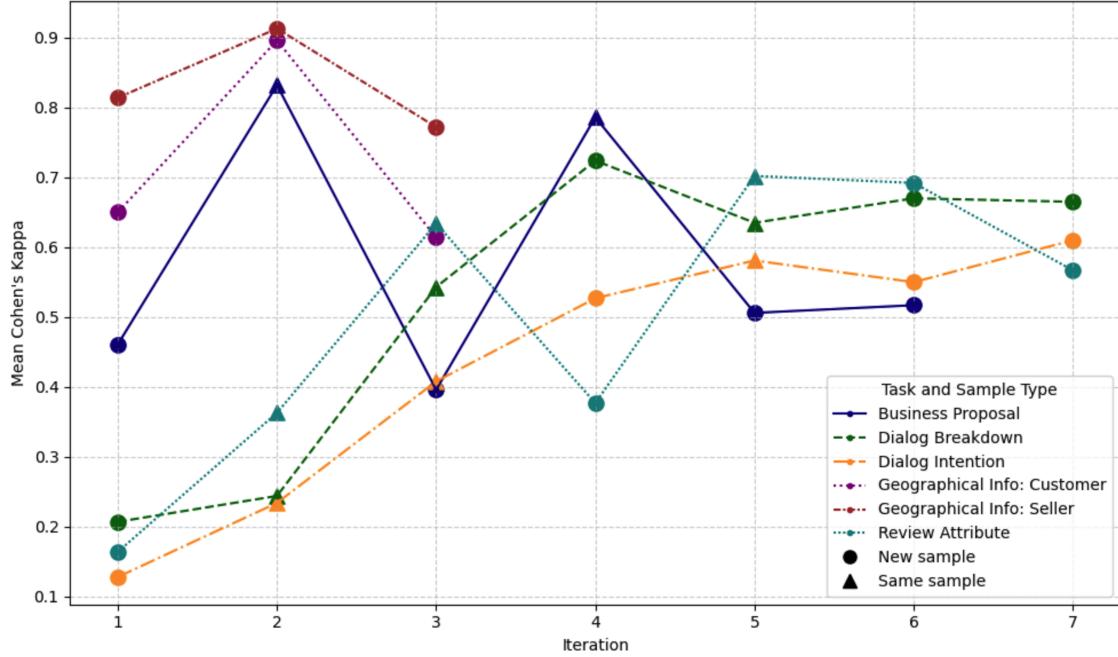


Figure 4 Development of Annotation Guidelines: Mean Cohen’s Kappa Across Iterations by Task

5.1.2. The prescriptive guidelines could be complex and require multiple iterations.

Figure 4 also highlights that achieving a high level of inter-annotator agreement often requires multiple iterations of refinement. For instance, tasks like dialog analysis and review attribute detection initially showed low agreement but improved significantly over successive iterations. Iterative testing and adaptation are necessary to address ambiguities and ensure consistent interpretation among annotators.

5.1.3. Expert-labeled baseline is a much higher standard than crowdsourced worker-labeled baseline.

For the business proposal evaluation task, we established the expert baseline by having the RAs who developed the annotation guidelines annotate the baseline sample. Subsequently, we provided the same annotation guidelines to three crowdsourced workers and instructed them to annotate the same sample. Among the three RAs, the mean Cohen’s Kappa was 0.517, indicating a moderate agreement level. However, the three crowdsourced workers achieved only a mean Cohen’s Kappa of 0.376, demonstrating their limited ability to understand and annotate in an aligned manner. To further evaluate, we aggregated the annotations from the three

crowdsourced workers using a majority-vote approach, treating this collaborative annotation as a single output comparable to individual LLM annotations. We then calculated the Cohen’s Kappa between each LLM’s annotation and the crowdsourced workers’ aggregated annotation against the ground truth (assumed to be the majority vote by the expert annotators). As shown in Figure 5, the crowdsourced workers’ labels achieved an agreement level similar to that of median-performing LLMs, such as Gemini 1.5 Pro. These findings highlight that for LLM performance evaluation, the two baselines—expert-labeled and crowdsourced worker-labeled—represent substantially different standards. Expert-labeled baselines tend to set a much higher baseline. Therefore, we recommend that researchers prioritize expert-labeled baselines when evaluating LLM performance to ensure rigorous and reliable assessments.

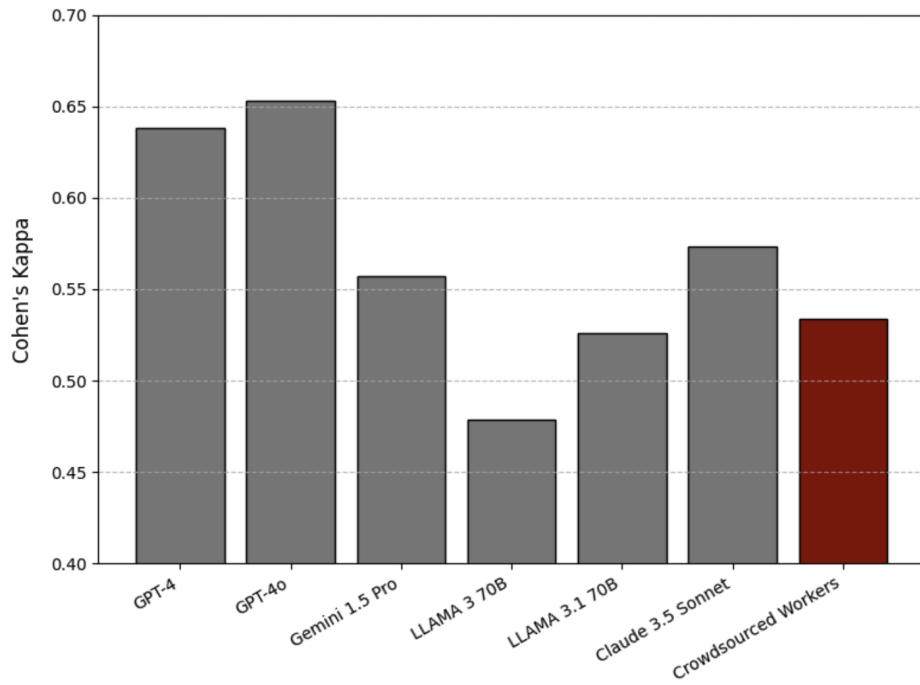


Figure 5 LLMs vs. Crowdsourced Workers Comparing to Expert Baseline (Business Proposal Evaluation Task)

5.2. Prompt Optimization

For prompt optimization, we fixed the annotation guidelines and focused on the meta-prompt design. Specifically, we explored three prompting strategies—base prompt, persona, and chain-of-thought—while varying their placement (system role versus user role) to generate six distinct

prompts. We then tested these six prompts across four models in the business proposal evaluation task.

As shown in Table 1, the best-performing prompts for all models are those where annotation guidelines were provided in the system role.¹³ Additionally, although the rank order of prompt performance varies across models, the observed performance differences are relatively small. The findings indicate that for researchers constrained by cost and time, the default prompt or the persona strategy with guidelines in the system role is sufficient. This streamlined approach balances resource efficiency with robust performance outcomes, avoiding unnecessary complexity without compromising effectiveness.

Table 1 Model Performance under Different Prompts (Business Proposal Evaluation Task)

Model	Guidelines in System Role			Guidelines in User Role		
	Base	Persona	CoT	Base	Persona	CoT
GPT-4o	0.667	0.63	0.595	0.619	0.561	0.582
Claude 3.5 Sonnet	0.571	0.502	0.618	0.526	0.57	0.574
Gemini 1.5 Pro	0.559	0.5	0.475	0.544	0.541	0.506
LLaMA 3.1 70B	0.512	0.552	0.508	0.545	0.545	0.477

Note: The values represent Cohen's Kappa scores between LLM annotations and human ground truth

5.3. Model Comparison

This section examines the performance of various LLMs across seven case studies, focusing on identifying task-specific strengths and limitations.¹⁴ Prompt iteration was conducted exclusively using GPT-4 Turbo, and once an optimal prompt was developed, it was consistently applied across all other models.

5.3.1. LLM suitability varies across tasks. The results, as shown in Table 2, reveal that the suitability of LLMs varies significantly across tasks. This underscores the importance of task-specific LLM performance evaluation.

¹³ We also verified this through the regression-based approach.

¹⁴ The geographical information extraction task is excluded from the table as it was tested on only one model. For the seller-side geographical information extraction task, GPT-4o achieves a Cohen's Kappa of 0.885, while for the customer-side geographical information extraction task, GPT-4o achieves a Cohen's Kappa of 0.589.

In standard NLP tasks such as sentiment analysis, all evaluated models demonstrate high performance, closely aligning with human annotations and achieving a Cohen’s Kappa score of 0.9 or higher. This strong agreement level underscores the robustness of these models in handling well-defined and straightforward tasks. For tasks like business proposal evaluation, review attribute detection, language toxicity detection, and criticism stance detection, LLMs exhibit moderate agreement with human annotators, with a Cohen’s Kappa score around 0.5. This performance suggests that the models are capable of effectively handling a variety of scenarios, including both single-label and multi-label classification tasks.

However, the models struggle significantly in more complex tasks, such as dialog intent analysis. This task, which involves multi-label classification across approximately ten intention classes, results in a Cohen’s Kappa score of around 0.2. Such low agreement highlights substantial limitations in the models’ ability to process nuanced and multidimensional interactions. The stark contrast in performance between sentiment analysis and dialog intent analysis emphasizes that while LLMs perform well in structured, straightforward scenarios, they remain inadequate for tasks requiring intricate understanding and contextual sensitivity. For these more challenging tasks, human annotation—whether through crowdsourced workers or trained RAs—continues to be a more reliable solution.

Table 2 Cross-Model Performance Comparison

Task	GPT-4 Turbo	GPT-4o	Gemini 1.5 Pro	LLaMA 3 70B	Claude 3.5 Sonnet
Business Proposal Evaluation	0.638	0.653	0.557	0.479	0.573
Review Attribute Detection	0.416	0.479	0.346	0.429	0.152
Dialog Intent Classification	0.203	0.121	0.183	0.196	0.141
Dialog Breakdown Analysis	0.532	0.568	0.732	0.296	0.689
Language Toxicity Detection	0.435	0.471	0.407	0.495	0.390
Critism stance detection	0.52	0.54	0.55	0.5	0.57
Sentiment Analysis	0.902	0.918	0.885	0.900	0.822

Note: The values represent Cohen’s Kappa scores between LLM annotations and human ground truth.

5.3.2. Relative performance of models varies across tasks. Again as shown in Table 2, the relative performance of the tested models demonstrates considerable task dependency, reinforcing the idea that no single model consistently outperforms others across all scenarios.

Among the models, GPT-4o emerges as the strongest performer in tasks such as business proposal evaluation, review attribute detection, and sentiment analysis. It also shows competitive performance in other areas but does not dominate uniformly. For instance, in language toxicity detection task, LLaMA 3 70B slightly outperforms GPT-4 Turbo, suggesting that open-source models can rival proprietary alternatives in certain specialized tasks. In addition, Gemini 1.5 Pro achieves the highest score in dialog breakdown analysis, and Claude 3.5 Sonnet performs best in criticism stance detection. These results suggest that it is often necessary for researchers to test multiple models. Practically, for researchers on tight budgets, open-source models like LLaMA 3 70B offer a cost-effective yet competitive option. Testing such models against performance thresholds before committing to more expensive alternatives is a prudent strategy.

5.3.3. Identifying a set of LLMs with statistical equivalence. To rigorously identify a set of models with statistical equivalence, we applied the regression-based approach outlined in Section 3.2.4. Figure 6 presents the coefficient plot, treating each model as a binary treatment variable and using GPT-4o as the omitted baseline for comparison. By design, the regression estimates represent the differences between each model’s accuracy and that of the baseline model. The standard errors and confidence intervals provide the unique insights derived from the regression. Specifically, the 95% confidence intervals for three models include the value 0, indicating that their performance is not statistically different from the baseline model at the 95% confidence level. However, the remaining three models, Gemini 1.0 Pro, LLaMA 3 70B and LLaMA 3.1 70B, exhibit confidence intervals that do not overlap with 0, and their estimates are lower than 0, implying that their performance is statistically worse than the baseline.

This analysis enables us to infer that, for the focal task (business proposal evaluation), the following models (GPT-4 Turbo, Gemini 1.5 Pro, Claude 3.5 Sonne) can be considered statistically equivalent to the baseline (GPT-4o). In other words, their generated results achieve an accuracy score that is statistically indistinguishable from that of GPT-4o when compared to human baselines. Consequently, we have successfully identified a set of models that can reliably reproduce the full population annotation results if used as alternatives to the baseline model.

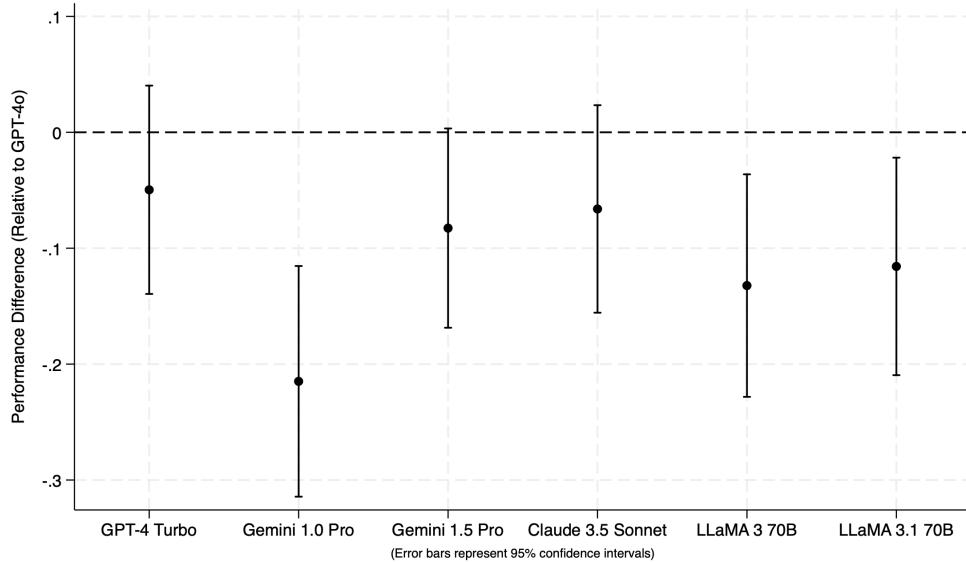


Figure 6 Regression-based Performance Comparison Across Models (Business Proposal Evaluation Task)

6. Conclusions and Discussion

In this study, we propose the SILICON workflow, an innovative approach to guiding the application of LLMs for text annotation tasks, particularly within the management research domain. The workflow integrates an iterative and transparent process for developing annotation guidelines and establishing human annotation baselines, alongside comprehensive prompt optimization and model selection guidance. This approach aims to help researchers conduct valid and reproducible studies using LLMs. We apply this workflow across seven common management research scenarios, validating its efficacy and offering the following recommendations for researchers:

Develop Clear Annotation Guidelines: Before exploring the use of LLMs for text annotation in a specific scenario or task, researchers must ensure the existence of well-defined annotation guidelines that at least a set of experts can agree upon. If such guidelines do not exist, researchers can leverage the SILICON workflow to develop them systematically.

Establish Human Annotation Baselines: As acknowledged in prior research (e.g., Pangakis et al. 2023), evaluating LLMs against human annotation baselines is critical. We further advocate this argument and, more importantly, emphasize that who develops such human baselines matters. Specifically, we demonstrate that expert-developed baselines uphold significantly higher standards

compared to those developed by crowdsourced workers. Therefore, we argue that researchers should prioritize creating expert baselines for robust comparisons.

Optimize Prompts Using Fixed Guidelines and Meta-Prompts: When optimizing prompts for LLMs, it is essential for the sake of fair comparison to fix the content of the annotation guidelines and refine optimization efforts through meta-prompts. There are various strategies for meta-prompt optimization, such as choosing the position for the annotation guidelines, using persona settings, and employing chain-of-thought prompting. While testing multiple prompts is beneficial if the budget allows, we recommend the following practical approach: place the annotation guidelines in the system role of the LLM rather than the user role. Using either a simple prompt that includes only the annotation guidelines with formatting instructions or enhancing it by adding a persona is often sufficient.

Test Multiple LLMs: Given that the performance of different LLMs varies across tasks, it is often necessary to test multiple models for the focal task. There is no universally best-performing LLM, and model selection should be task-specific to ensure optimal results.

Ensure Reproducibility Using Regression-Based Approaches: For researchers aiming to demonstrate the reproducibility of LLM-based text annotation results—such that similar results can be achieved even with alternative LLMs—we propose a regression-based approach to quantify and validate reproducibility.

Although our primary focus has been on the management field, the SILICON workflow is generalizable to other disciplines seeking to use LLMs as a tool for text annotation. However, it is crucial to acknowledge the differences between disciplines that may influence the application of the SILICON workflow. For instance, different fields may have varying standards for the level of agreement required in annotation guidelines. In disciplines where precise ground truth is critical—such as those involving ethics, morality, or safety—researchers may need to invest significant effort in developing highly prescriptive annotation guidelines.

A key assumption of the SILICON workflow is that researchers aim to adopt a prescriptive approach to address annotation challenges, as detailed in Section 2.1. Consequently, a limitation

of our method is that it focuses exclusively on using LLMs to replicate “prescriptive” judgments made by annotators. In contexts such as psychology, capturing the diverse perspectives of human participants may be the primary goal for researchers. Studies have highlighted the high risk of false significance when using LLMs to replicate human judgments (Cui et al. 2024). Therefore, if the objective of the annotations is to reflect the underlying variability in human judgments influenced by individual backgrounds, the SILICON workflow may not be suitable. Moreover, there is an ongoing debate across business, psychology, and NLP communities regarding when and how effectively LLMs can replicate human judgments. While potential extensions to the SILICON workflow could address these concerns, such discussions are beyond the scope of this work.

References

- Aguinis H, Villamor I, Ramani RS (2021) MTurk Research: Review and Recommendations. *Journal of Management* 47(4):823–837.
- Antoniou C, Doukas JA, Subrahmanyam A (2016) Investor Sentiment, Beta, and the Cost of Equity Capital. *Management Science* 62(2):347–367.
- Artstein R (2017) Inter-annotator Agreement. Ide N, Pustejovsky J, eds., *Handbook of Linguistic Annotation*, 297–313 (Dordrecht: Springer Netherlands), ISBN 978-94-024-0881-2.
- Autor D (2014) Polanyi’s Paradox and the Shape of Employment Growth. Working Paper 20485, National Bureau of Economic Research.
- Banerjee S, Dellarocas C, Zervas G (2021) Interacting User-Generated Content Technologies: How Questions and Answers Affect Consumer Reviews. *Journal of Marketing Research* 58(4):742–761.
- Basile V, Fell M, Fornaciari T, Hovy D, Paun S, Plank B, Poesio M, Uma A (2021) We Need to Consider Disagreement in Evaluation. Church K, Liberman M, Kordonis V, eds., *Proceedings of the 1st Workshop on Benchmarking: Past, Present and Future*, 15–21 (Online: Association for Computational Linguistics).
- Bavaresco A, Bernardi R, Bertolazzi L, Elliott D, Fernández R, Gatt A, Ghaleb E, Giulianelli M, Hanna M, Koller A, Martins AFT, Mondorf P, Neplenbroek V, Pezzelle S, Plank B, Schlangen D, Suglia A, Surikuchi AK, Takmaz E, Testoni A (2024) LLMs instead of Human Judges? A Large Scale Empirical Study across 20 NLP Evaluation Tasks.
- Boussioux L, N Lane J, Zhang M, Jacimovic V, Lakhani KR (2023) The Crowdless Future? How Generative AI Is Shaping the Future of Human Crowdsourcing. *SSRN Electronic Journal*.
- Bronnenberg BJ, Klein TJ, Xu Y (2024) Consumer Time Budgets and Grocery Shopping Behavior. *Management Science* 70(3):1596–1612.
- Cao J, Liang H, Zhan X (2019) Peer Effects of Corporate Social Responsibility. *Management Science* 65(12):5487–5503.

- Carlson N, Burbano V (2024) The Use of LLMs to Annotate Data in Management Research: Warnings, Guidelines, and an Application to Organizational Communication. *SSRN Electronic Journal*.
- Chakraborty I, Kim M, Sudhir K (2022) Attribute sentiment scoring with online text reviews: Accounting for language structure and missing attributes. *Journal of Marketing Research* 59(3):600–622.
- Choudhury P, Wang D, Carlson NA, Khanna T (2019) Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles. *Strategic Management Journal* 40(11):1705–1732.
- Cohen J (1968) Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. *Psychological Bulletin* 70(4):213–220.
- Cui Z, Li N, Zhou H (2024) Can AI Replace Human Subjects? A Large-Scale Replication of Psychological Experiments with LLMs.
- Deng C, Ravichandran T (2023) Managerial Response to Online Positive Reviews: Helpful or Harmful? *Information Systems Research*.
- Dillion D, Mondal D, Tandon N, Gray K (2024) Large Language Models as Moral Experts? GPT-4o Outperforms Expert Ethicist in Providing Moral Guidance.
- Doshi AR, Bell JJ, Mirzayev E, Vanneste BS (2024) Generative artificial intelligence and evaluating strategic decisions. *Strategic Management Journal* smj.3677.
- Fišar M, Greiner B, Huber C, Katok E, Ozkes AI, and the Management Science Reproducibility Collaboration (2024) Reproducibility in Management Science. *Management Science* 70(3):1343–1356.
- Frankel R, Jennings J, Lee J (2022) Disclosure Sentiment: Machine Learning vs. Dictionary Methods. *Management Science* 68(7):5514–5532.
- Ghose A, Ipeirotis PG (2011) Estimating the Helpfulness and Economic Impact of Product Reviews: Mining Text and Reviewer Characteristics. *IEEE Transactions on Knowledge and Data Engineering* 23(10):1498–1512.
- Gilardi F, Alizadeh M, Kubli M (2023) ChatGPT Outperforms Crowd Workers for Text-Annotation Tasks. *Proceedings of the National Academy of Sciences* 120(30):e2305016120.
- Goodman JK, Paolacci G (2017) Crowdsourcing Consumer Research. *Journal of Consumer Research* 44(1):196–210.
- Higashinaka R, Funakoshi K, Kobayashi Y, Inaba M (2016) The dialogue breakdown detection challenge: Task description, datasets, and evaluation metrics. Calzolari N, Choukri K, Declerck T, Goggi S, Grobelnik M, Maegaard B, Mariani J, Mazo H, Moreno A, Odijk J, Piperidis S, eds., *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16)*, 3146–3150 (Portorož, Slovenia: European Language Resources Association (ELRA)).
- Homburg C, Ehm L, Artz M (2015) Measuring and Managing Consumer Sentiment in an Online Community Environment. *Journal of Marketing Research* 52(5):629–641.
- Hong Y, Peng J, Burtsch G, Huang N (2021) Just DM Me (Politely): Direct Messaging, Politeness, and Hiring Outcomes in Online Labor Markets. *Information Systems Research* 32(3):786–800.
- Hovy E, Lavid J (2010) Towards a ‘science’of corpus annotation: a new methodological challenge for corpus linguistics. *International journal of translation* 22(1):13–36.

- Hu T, Collier N (2024) Quantifying the Persona Effect in LLM Simulations.
- Humphreys A, Wang RJH (2018) Automated Text Analysis for Consumer Research. *Journal of Consumer Research* 44(6):1274–1306.
- Jaccard P (1908) Nouvelles recherches sur la distribution florale. *Bull. Soc. Vaud. Sci. Nat.* 44:223–270.
- Jackson JC, Watts J, List JM, Puryear C, Drabble R, Lindquist KA (2022) From text to thought: How analyzing language can advance psychological science. *Perspectives on Psychological Science* 17(3):805–826.
- Kwark Y, Lee GM, Pavlou PA, Qiu L (2021) On the Spillover Effects of Online Product Reviews on Purchases: Evidence from Clickstream Data. *Information Systems Research* 32(3):895–913.
- Landis JR, Koch GG (1977) The Measurement of Observer Agreement for Categorical Data. *Biometrics* 33(1):159.
- Lee D, Hosanagar K (2021) How Do Product Attributes and Reviews Moderate the Impact of Recommender Systems Through Purchase Stages? *Management Science* 67(1):524–546.
- Lee D, Hosanagar K, Nair HS (2018) Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook. *Management Science* 64(11):5105–5131.
- Lee N, Bollinger B, Staelin R (2023a) Vertical Versus Horizontal Variance in Online Reviews and Their Impact on Demand. *Journal of Marketing Research* 60(1):130–154.
- Lee S, DeLucia A, Nangia N, Ganedi P, Guan R, Li R, Ngaw B, Singhal A, Vaidya S, Yuan Z, Zhang L, Sedoc J (2023b) Common Law Annotations: Investigating the Stability of Dialog System Output Annotations. Rogers A, Boyd-Graber J, Okazaki N, eds., *Findings of the Association for Computational Linguistics: ACL 2023*, 12315–12349 (Toronto, Canada: Association for Computational Linguistics).
- Leek LC, Bischi S, Freier M (2024) Introducing Textual Measures of Central Bank Policy-Linkages Using ChatGPT.
- Liu X, Lee D, Srinivasan K (2019) Large-Scale Cross-Category Analysis of Consumer Review Content on Sales Conversion Leveraging Deep Learning. *Journal of Marketing Research* 56(6):918–943.
- Loughran T, McDonald B (2014) Measuring Readability in Financial Disclosures. *The Journal of Finance* 69(4):1643–1671.
- Manning BS, Zhu K, Horton JJ (2024) Automated Social Science: Language Models as Scientist and Subjects.
- Matook S, Dennis AR, Wang YM (2022) User Comments in Social Media Firestorms: A Mixed-Method Study of Purpose, Tone, and Motivation. *Journal of Management Information Systems* 39(3):673–705.
- Mayya R, Ye S, Viswanathan S, Agarwal R (2021) Who Forgoes Screening in Online Markets and Why? Evidence from Airbnb. *MIS Quarterly* 45(4):1745–1776.
- Melumad S, Inman JJ, Pham MT (2019) Selectively Emotional: How Smartphone Use Changes User-Generated Content. *Journal of Marketing Research* 56(2):259–275.
- Obermeier D, Mayya R (2024) Decentralized Governance as an Open Platform Strategy: An Empirical Study of Devolving Controls through DAOs .
- Oh H, Goh KY, Phan TQ (2023) Are You What You Tweet? The Impact of Sentiment on Digital News Consumption and Social Media Sharing. *Information Systems Research* 34(1):111–136.

- Pangakis N, Wolken S, Fasching N (2023) Automated Annotation with Generative AI Requires Validation .
Passonneau R (2006) Measuring agreement on set-valued items (MASI) for semantic and pragmatic annotation. Calzolari N, Choukri K, Gangemi A, Maegaard B, Mariani J, Odijk J, Tapias D, eds., *Proceedings of the fifth international conference on language resources and evaluation (LREC'06)* (Genoa, Italy: European Language Resources Association (ELRA)).
- Peng H, Romero DM, Horvát EÁ (2022) Dynamics of cross-platform attention to retracted papers. *Proceedings of the National Academy of Sciences* 119(25):e2119086119.
- Rathje S, Mirea DM, Sucholutsky I, Marjeh R, Robertson C, Van Bavel JJ (2024) GPT is an effective tool for multilingual psychological text analysis. *Proceedings of the National Academy of Sciences* 121(34):121 (34) e2308950121.
- Rosette AS, Carton AM, Bowes-Sperry L, Hewlin PF (2013) Why Do Racial Slurs Remain Prevalent in the Workplace? Integrating Theory on Intergroup Behavior. *Organization Science* 24(5):1402–1421.
- Rottger P, Vidgen B, Hovy D, Pierrehumbert J (2022) Two Contrasting Data Annotation Paradigms for Subjective NLP Tasks. Carpuat M, de Marneffe MC, Meza Ruiz IV, eds., *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, 175–190 (Seattle, United States: Association for Computational Linguistics).
- Saha P, Garimella K, Kalyan NK, Pandey SK, Meher PM, Matheu B, Mukherjee A (2023) On the Rise of Fear Speech in Online Social Media. *Proceedings of the National Academy of Sciences* 120(11):e2212270120.
- Sap M, Card D, Gabriel S, Choi Y, Smith NA (2019) The Risk of Racial Bias in Hate Speech Detection. Korhonen A, Traum D, Màrquez L, eds., *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 1668–1678 (Florence, Italy: Association for Computational Linguistics).
- Sen C, Hartvigsen T, Yin B, Kong X, Rundensteiner E (2020) Human Attention Maps for Text Classification: Do Humans and Neural Networks Focus on the Same Words? *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, 4596–4608 (Online: Association for Computational Linguistics).
- Shi L, Mayya R, Ye S (2023) Location Divide in Digital Platforms? Evidence from a Natural Experiment. *SSRN Electronic Journal* .
- Shi ZJ, Liu X, Srinivasan K (2022) Hype News Diffusion and Risk of Misinformation: The Oz Effect in Health Care. *Journal of Marketing Research* 59(2):327–352.
- Sibai O, Luedicke MK, De Valck K (2024) Why Online Consumption Communities Brutalize. *Journal of Consumer Research* ucae022.
- Stolcke A, Ries K, Coccaro N, Shriberg E, Bates R, Jurafsky D, Taylor P, Martin R, Van Ess-Dykema C, Meteer M (2000) Dialogue Act Modeling for Automatic Tagging and Recognition of Conversational Speech. *Computational Linguistics* 26(3):339–374.
- Törnberg P (2024) Best Practices for Text Annotation with Large Language Models.
- Veselovsky V, Ribeiro MH, West R (2023) Artificial Artificial Intelligence: Crowd Workers Widely Use Large Language Models for Text Production Tasks.
- Wei J, Wang X, Schuurmans D, Bosma M, Ichter B, Xia F, Chi E, Le Q, Zhou D (2023) Chain-of-Thought Prompting Elicits Reasoning in Large Language Models.

- Wilkerson J, Casas A (2017) Large-scale computerized text analysis in political science: Opportunities and challenges. *Annual Review of Political Science* 20:529–544.
- Xie C, Chen C, Jia F, Ye Z, Lai S, Shu K, Gu J, Bibi A, Hu Z, Jurgens D, Evans J, Torr P, Ghanem B, Li G (2024) Can Large Language Model Agents Simulate Human Trust Behavior? (38th Conference on Neural Information Processing Systems).
- Yang M, Ren Y, Adomavicius G (2019) Understanding User-Generated Content and Customer Engagement on Facebook Business Pages. *Information Systems Research* 30(3):839–855.
- Yeverechyan D, Mayya R, Oestreicher-Singer G (2024) The Impact of Large Language Models on Open-Source Innovation: Evidence from GitHub Copilot. *SSRN Electronic Journal*.
- Zhang C, D'Haro LF, Chen Y, Zhang M, Li H (2024) A Comprehensive Analysis of the Effectiveness of Large Language Models as Automatic Dialogue Evaluators.
- Zhang K, Bhattacharyya S, Ram S (2016) Large-Scale Network Analysis for Online Social Brand Advertising. *MIS Quarterly* 40(4):849–868.

Appendix A: Measurement of Agreement Rate: Cohen’s Kappa

To measure agreement, one simple way is counting the raw number of matching annotations. However, the raw agreement fails to account for agreements that might occur by chance. This can lead to misleading conclusions, especially in cases where the likelihood of random agreement is high (Lee et al. 2023b). To overcome this limitation, we employed Cohen’s Kappa (κ), which measures the level of agreement between two annotators while adjusting for chance agreement (Cohen 1968). The formula for Cohen’s Kappa is given by:

$$\kappa = \frac{P_o - P_e}{1 - P_e},$$

where P_o is the relative observed agreement among raters, and P_e is the hypothetical probability of agreement by chance. Specifically, $\kappa = 1$ indicates perfect agreement. $\kappa = 0$ indicates agreement no better than chance. $\kappa < 0$ suggests less agreement than would be expected by chance. A Cohen’s Kappa of 0.6 to 0.8 is commonly regarded as a threshold for sufficient inter-annotator agreement (Landis and Koch 1977).

In our multi-label classification task, annotators could assign multiple distinct labels (referred to as “units”) to a single item (e.g., a social media post). We define the overall label(s) assigned to an item as a “set”. For instance, in the toxicity detection task, there are in total three units, “fearspeech”, “hatespeech”, and “normal”, and a set could be “fearspeech, hatespeech”. It is apparent that the agreement level between “fear-speech, hatespeech” and “fearspeech” should be higher than that between “hatespeech” and “fearspeech”. To account for this, we use Weighted Cohen’s Kappa (Cohen 1968), which is given by

$$\kappa = 1 - \frac{\sum_{i=1}^k \sum_{j=1}^k w_{ij}x_{ij}}{\sum_{i=1}^k \sum_{j=1}^k w_{ij}m_{ij}},$$

where w_{ij} is the weight matrix, x_{ij} is the observed matrix, and m_{ij} is the expected matrix.

We follow Passonneau (2006) to derive the weight matrix W for our calculations. The weight w ranges from 0 (identical sets) to 1 (disjoint sets). The weight w between two sets P and Q is defined as:

$$w = 1 - J \cdot M,$$

where J is the Jaccard metric (Jaccard 1908) and M represents monotonicity. Specifically, J measures the size difference between two sets, independently of their structural relationship. It is calculated as the ratio of the cardinality of the intersection to the cardinality of the union of the two sets. J ranges from 0 (disjoint sets) to 1 (identical sets). The M term captures the structural relationship between sets: if two sets Q and

P are identical, M is 1; if one set is a subset of the other, M is 2/3; if the intersection and the two set differences are all non-null, then M is 1/3; if the sets are disjoint, M is 0. Altogether, the weight w reflects both the size difference and the structural relationship between the two sets. For instance, in the language toxicity detection task, the weight between sets “fearspeech” and “hatespeech” is 1, and the weight between “fearspeech” and “fearspeech, hatespeech” is 2/3.

Appendix B: A Regression-based Approach to Compare LLM Annotation Performance

Consider the scenario where we use the same prompt across multiple models applied to the same text sample.¹⁵ Our goal is to statistically compare model performances and identify models with equivalent results. Specifically, we aim to determine whether a model’s performance metric differs significantly from others or if certain models yield statistically indistinguishable performance metrics.

In this setting, there are two sources of uncertainty:

1. Sampling uncertainty: This arises from inferring population parameters (e.g., differences in LLM performance across models) based on the human baseline sample, which is randomly drawn from the human baseline.
2. Stochastic output uncertainty: This stems from the non-deterministic nature of LLM outputs. The literature (e.g., Pangakis et al. 2023) documents this variability, and common approaches to account for this uncertainty include running the model multiple times and calculating the consistency of its annotation results.

Our focus is on addressing the first source of uncertainty. Instead of computing overall performance metrics for each model and comparing them with pairwise tests or bootstraps, we propose a regression-based approach.

Suppose we use J models to annotate a sample with I items (e.g., a sample consisting of I business proposals). We treat each model as a distinct “treatment” and aim to assess the “treatment effect” of one model compared to a baseline model. Denoting the model by j (1, 2, ..., J) and the item by i (1, 2, ..., I),

¹⁵ This approach in essence is about comparing LLM annotation performance across different treatments. Treatments could be different models or different prompts, and the same logic outlined here applies to both scenarios.

the unit of analysis is the item-model pair, ij . The dependent Variable ($Matched_{ij}$) is an indicator variable equal to 1 if the model j 's label for item i matches the human ground truth, and 0 otherwise.¹⁶

We then regress the dependent variable $Matched_{ij}$ on all treatment dummies, excluding one due to perfect collinearity. The regression equation is:

$$Match_{ij} = \alpha_0 + \alpha_1 \mathbb{1}(j=1) + \alpha_2 \mathbb{1}(j=2) + \dots + \alpha_{J-1} \mathbb{1}(j=J-1) + \epsilon_{ij}. \quad (1)$$

Here, the J -th treatment is omitted as the baseline. The coefficients are interpreted as follows:

$$\begin{aligned} \alpha_0 &= E(Matched_{ij}|j=J) \\ \alpha_1 &= E(Matched_{ij}|j=1) - \alpha_0 \\ \alpha_2 &= E(Matched_{ij}|j=2) - \alpha_0 \\ &\dots \\ \alpha_{J-1} &= E(Matched_{ij}|j=J-1) - \alpha_0 \end{aligned} \quad (2)$$

Crucially, we cluster standard errors at the item level to account for the fact that each item i is “tested” multiple times—once per model. By design, the regression estimates represent the differences between each model’s accuracy score and that of the baseline model. Hypotheses can be tested using this framework, such as (1) joint test: $H_a: \alpha_1 = \alpha_2 = \alpha_3 = \dots = \alpha_{J-1} = 0$, using F-statistics, and (2) individual tests: $H_{b1}: \alpha_1 = 0$, $H_{b2}: \alpha_2 = 0, \dots, H_{b(J-1)}: \alpha_{J-1} = 0$.

This regression method has some advantages over direct comparison of sample-metric. First, a single sample metric (like overall accuracy or Kappa for each model) requires pairwise (or multiple) tests to compare models, ignoring item-level nuances. The regression approach uses the entire item-model structure, and allows us to account for within-item interdependence. Second, we can test all models simultaneously (via an F-test on all treatment dummy coefficients). This reduces the complexity of multiple pairwise comparisons and type I error concerns.

Additionally, under this framework, the second source of uncertainty (stochasticity in LLM outputs) can also be addressed with additional assumptions. Specifically, we consider that LLMs aim to produce an

¹⁶ This binary “matched” measure is straightforward and easily interpretable at the item level. When aggregated across items, it provides the model’s accuracy. However, a slight discrepancy exists since in our case studies, we use Cohen’s Kappa to account for chance agreement. This adjustment is made because Cohen’s Kappa is a chance-corrected measure calculated over all items, which makes it less intuitive at the per-item level. Nonetheless, applying a Kappa-like transformation to derive the dependent variable would still align with the same regression logic.

“intended output”¹⁷ but sometimes generate a different “actual output” due to non-determinism. From a regression perspective, this discrepancy can be treated as a form of measurement error. Assuming the measurement error is independently and identically distributed (i.i.d.), the regression estimates remain unbiased when the sample size is sufficiently large.

Appendix C: Development of Annotation Guidelines

Here, we detail the process of creating annotation guidelines for the dialog analysis task, as shown in Table 3. We recruit three undergraduate RAs to undertake this iterative process. Initially, they receive an overview of the task, including the contextual background and labels for the two classification tasks. The RAs independently label a small sample and then discuss their results via Zoom, emphasizing points of disagreement and refining label definitions (Iteration 1). Following this initial meeting, the RAs annotate the same shuffled sample twice more, meeting after each annotation to discuss their results (Iterations 2 and 3). After reaching an agreement rate threshold in their third iteration, they move to a new sample, repeating the annotation and meeting process twice (Iterations 4 and 5). In their next sample, they achieve the agreement threshold on their first attempt (Iteration 6), concluding the iteration process. Finally, the RAs meet to consolidate their independent annotation guidelines and annotate a larger sample to establish a human baseline. Throughout the process, their mean Cohen’s Kappa for the intent classification task improves from 0.128 to 0.61, and their agreement for breakdown analysis increases from 0.207 to 0.665. The annotation guidelines and human annotation baseline are further used in the next phase of SILICON: optimizing prompts for LLMs and testing multiple LLMs’ performance.

The processes for business proposal evaluation, geographical information extraction, and review attribute detection tasks follow the same approach, wherein we recruit three RAs for each task to go through the iterative process. The details are summarized in Tables 4 through 6.

¹⁷ One could argue that the intended output is the one with the highest probability of being generated by the LLM model when the temperature is set to 0. However, we take the stance that the intended output may not necessarily align with the output generated under this condition. This difference is not the focus of the study, and we leave its discussion for future work.

Table 3 Development of Annotation Guidelines for Dialog Analysis Task

Iteration	Task	Number of conversations	Number of utterances	Intent Anaylsis Mean Cohen's Kappa	Breakdown Analysis Mean Cohen's Kappa
1	New sample	5	81	0.128	0.207
2	Same shuffled sample as 1	5	81	0.234	0.244
3	Same shuffled sample as 1	5	81	0.408	0.543
4	New sample	6	101	0.527	0.724
5	Same shuffled sample as 4	6	101	0.581	0.635
6	New sample	6	100	0.550	0.670
-	New large sample (the human baseline)	18	195	0.61	0.665

Table 4 Development of Annotation Guidelines for Business Proposal Evaluation

Iteration	Task	Number of proposals	Mean Cohen's Kappa
1	New sample	50	0.461
2	Same shuffled sample as 1	50	0.832
3	New sample	49	0.396
4	Same shuffled sample as 3	49	0.786
5	New sample	50	0.506
-	New large sample (the human baseline)	121	0.517

Table 5 Development of Annotation Guidelines for Geographical Information Extraction Task

Iteration	Task	Number of product pages	Seller Disclosed Location Mean Cohen's Kappa	Customer Disclosed Loaction Mean Cohen's Kappa
1	New sample	32	0.814	0.650
2	New sample	32	0.913	0.896
-	New large sample (the human baseline)	118	0.772	0.614

Table 6 Development of Annotation Guidelines for Review Attribute Detection Task

Iteration	Task	Number of Reviews	Mean Cohen's Kappa
1	New sample	67	0.164
2	Same shuffled sample as 1	67	0.363
3	Same shuffled sample as 1	67	0.634
4	New sample	65	0.377
5	Same shuffled sample as 4	65	0.702
6	New sample	65	0.692
-	New large sample (the human baseline)	180	0.567

Appendix D: Adopted Prompts

The prompts presented here are used uniformly across all LLMs for each task. These prompts were selected following a testing procedure conducted using GPT-4 Turbo. For a detailed appendix containing all the prompts tested for each task, please contact the authors.

D.1. Business Proposal Evaluation

Business Proposal Evaluation

System Role: You are shown decentralized autonomous organization (DAO) proposals. Your task is to classify the proposals by their main function or intention. Please go through each proposal and categorize it into one of five different categories: Organizational, Business Model, Marketing, Functionality, and Security. If the proposal doesn't fit into either of these first five categories, then please classify it as "Other". After the specific definition of each category, in-depth examples are provided of proposals that would fall under each category directly after the specific case it is related to.

1. Organizational

If a proposal contains components in the following areas, categorize it as "Organizational".

- Proposals that appoint board members, form any sort of organizational body, or contain any discussion of forming a council.

Example: "Should we commence P12DAO to govern aspects of our daily operations to ensure a more engaging workspace decision-making?"

- Proposals giving certain users authority or permission over certain tasks without needing DAO approval.

Example: "Give the ability to the team to independently manage vault ceilings and emergency closing."

- Proposals regarding access changes like whitelisting/blacklisting certain users or tokens.

Example: "We propose to whitelist TOKEMAK on Stake DAO Liquid Lockers to allow them to lock SDT and vote with veSDT."

- Proposals related to budget allocation, funding, grants, requests for funds for dAPP or DAO-relevant initiatives only.

Example: "Should the following \$100,000 grant in the Sponsorship category be approved?"

- Proposals that discuss potential partnerships with other platforms, creators, or applications.

- Proposals that change the governance structure, bodies, process through who can vote in governance, changing the governance token, how governance decisions are made, and what can be voted on should be characterized as Organizational.

Example: "Canceling the staking in governance. The calculation of vote rights, performed by the Snapshot, and users only need to hold to obtain vote rights without any staking operation."

2. Business Model

If a proposal contains components in the following areas, categorize it as "Business Model".

- Proposals that contain any discussion relating to increasing/decreasing liquidity of token(s) within a liquidity pool, discussion relating to liquidity providers, changes in pool liquidity thresholds, or investing in relation to monetary value.

Example: "Bootstrap liquidity for \$ACX on Optimism through Velodrome."

- Proposals that discuss offering a new token within a liquidity pool, expanding accepted tokens in pools, increasing treasury diversity, or increasing deposit assets.

Example: "The goal of this proposal is to loan \$UNI to the \$oneUNI contract so that the minting ratio may be lowered from 98% to 80%."

- Proposals containing characteristics related to tokenization of assets, giveaways, or rewards based on token ownership, or buying/selling of NFTs.

Example: "Proposal to Boost the PMON-BUSD Farm, offer a new Syrup Pool from Poly-chain Monsters, beautifully animated cross-chain NFTs which can be unpacked from digital booster packs with \$PMON."

- Proposals containing modifications to lending or borrowing services, including modifications of deposit assets.

Example: “Enable wstETH deposits and facilitate borrowing by NFT collateral holders. Introduces wstETH as a deposit asset and can be lent by borrowers.”

- Proposals relating to changes to smart contract parameters focusing on fee collections/how much to collect as management fees including gauge weights and refunds to users.
- Proposals that include a software update (e.g., version 1 to version 2) that affects the value of the token, liquidity, or other smart contracts on the platform.

Example: “Updating Token Allowlist for ParaBoost.”

3. Marketing

If a proposal contains any discussion relating to promotional activities in the following area, categorize it as “Marketing”.

- Proposals containing components of promotional activities including filming advertising, creating advertising concepts, taking part in fairs, producing one-time events, online advertisements, and campaigns.

Example: “Is it possible to produce a TV ad?”

- Proposals relating to offering payouts for using a specific program or dApp through user claiming rewards from a set drop with wording such as “users claim your drop” that is promotional in nature.

Example: “LIDO drop According to tokenomics holders can receive a drop.”

- Proposals centered on merchandise production in terms of voting on designs for merchandise, what type of merchandise users prefer, avenues of selling merchandise, and offering new products in an in-game shop is considered widening a product offering.

Example: “Crewneck vote finals. Please vote for your favorite design.”

4. Functionality

If a proposal contains components in the following areas, categorize it as “Functionality”.

- Proposals related to gauges including adding a rewards system onto the platform, or any discussion of adding a new gauge.
- Proposals that include discussion of adding a new farm or pool should be considered an addition of a new feature. These are not changes to fix bugs or security issues, but instead may include offerance on another app/desktop to improve usability through the deployment of new code.

Example: “Rich Token Liquidity Pool. We have established the first RICH TOKEN Liquidity Pool.”

- Proposals expanding service offerings like adding new borrowing services or expanding the functionality of existing services should be classified under Functionality.

Example: “Add the location 15,63 to the Points of Interest.”

- Proposals that include a software update (e.g., version 1 to version 2) that adds new features (no mention of changing the value of assets or token on the platform).

Example: “Lido on Polygon V2 upgrade eases operator entry and exit, provides a smoother flow for users and network participants, reduces the gas needed for depositing.”

5. Security

If a proposal contains improving security measures in the following areas, categorize it as “Security”.

- Proposals fixing bugs and addressing security weaknesses with any discussion of boosting current security features and improving old measures.

Example: “OIP-118 Olympus Strategy formally approved the launch of a Range Bound Stability system. This OIP is to formalize a set of necessary permissions to launch the RBS system.”

- Proposals that include adopting measures to make it harder for external malicious actors to infect the application such as blocking spam proposals.
Example: “Delete Scam Proposals With Fake Links.”

6. Other

If the entirety of the proposal cannot be categorized in the other categories and if it contains any of the following components, please categorize it as “Other”.

- Proposals that only include a link without other descriptors and the title of the link is not sufficient to decide the category.
- Proposals asking for funds for purposes not related to the DAO or dAPP (e.g., to fund user’s education or living expenses).
- Proposals with terminology that is unclear that makes the wording of the proposal confusing, overtly informal language, or vague.
- Proposals in a language other than English.

User Role: Now you are given the `proposal_id`, title, and the content of the proposal. Read the proposal and output your answer in JSON format without explanation: `{"id": "<proposal_id>", "category": "<category>"}`. Here is the proposal: {proposal content}.

D.2. Review Attribute Detection

Review Attribute Detection

System Role:

You are a skilled review analyst capable of transforming unstructured review text into organized insights. You will be provided with a set of reviews, and you are tasked with annotating these samples via their attribute. You must tag each sample with all attributes that apply from a list of 6: *price*, *performance feature*, *reliability/durability*, *conformance*, *aesthetics*, and *perceived quality*. Follow the guidelines below to determine whether the attributes apply to the review. Remember that you should tag all that apply, meaning there may be multiple attributes that are applicable to the sample review that must be checked off. The provided examples for each attribute may take that attribute as their focus, but it does not mean that the same example would not also apply to another attribute.

Definitions by Attribute:

1. *Price*: For those reviews that mention price, or describe the product in relation to price (cheapness and/or expensiveness) of materials or components. Price can be tagged in multiple scenarios, including:

- *Actual price of the product*: A mention of how much the product cost, whether it was expensive, cheap, affordable, the right price, etc.
Example: “This product was very expensive.”
- *Value for money*: Mention of the price in relation to the product(s)’ performance and functions, or in relation to other similar products or previous purchases.
Example: “This is way too expensive for what it’s worth.”
- *Overall Mentions of Cheapness/Expensiveness*: Any mention of the perceived price of components, such as “cheap” or “expensive,” “costing a fortune,” or being a “bargain.”
Example: “Handle is cheap plastic, but other parts are expensive, quality materials.”
- *Coupons/Sales*: Any purchases made using coupons or if the product was mentioned to be on sale during purchase.
Example: “I got this product because it was on sale.”

2. *Performance Feature*: For those reviews with any mentions of the physical attributes/features of the product, regardless of what is described about those parts/components/features. Examples of performance features include:

- *Physical Parts*: Handles, buttons, cameras, fabric, ingredients, case, chargers, etc.
 - *Attributes*: Size, color (explicitly mentioned), and weight.
 - *Uses/Use Cases*: Different functions the product can perform.
Example: A radio may access both sports broadcasts and music broadcasts, making these two different “features.”
 - *Instructions and Set Up*: Describing whether or not something is “easy to use,” instructions provided with the product, or issues with set-up.
Example: “It’s easy to assemble and works perfectly.”
3. *Reliability/Durability*: This category deals with the quality of the product and includes:
- *Any Mention of Quality*: Whether the product is made well or poorly.
Example: “The materials are so cheap and break immediately.”
 - *Recommendation*: Recommending or not recommending the product to others.
Example: “I recommend this product to anyone who needs a new blanket!”
 - *Good or Bad Service/Warranty*: Service from a catalog or manufacturer.
Example: “Great customer service! They quickly replaced my product.”
 - *Feature Malfunctions Impacting Function*: Multiple faulty features integral to the product’s overall reliability.
Example: “This sheet set is terrible. The fabric of the blanket is rough, it is the wrong size, the pillow case will not go on right, the sheets slip off the bed.”
 - *Mention of Something Breaking/Tearing*:
Example: “The product is great overall, but the handle broke a week after purchase.”
 - *Inconsistency in the Product*: Features sometimes working and sometimes not.
Example: “Sometimes the light flickers, but it works most of the time.”
4. *Conformance*: For reviews that evaluate whether the product fulfills explicitly stated promises. These promises must come from product descriptions, names, advertisements, or reviews.
Example: “The reviews all said this product was great, but it’s such poor quality.”
5. *Aesthetics*: For any mentions of something appealing to the reviewer’s 5 senses (taste, touch, smell, hearing, sight) or design elements.
Example: “The kettle has a smart design.”
6. *Perceived Quality*: For reviews that directly compare the product to another product, which may include:
- *Comparison to the same product from previous purchases*.
Example: “This camera is much better than the one I bought last year.”
 - *Comparison to products of other brands or types*.
Example: “This is better than my old Polaroid camera.”
 - *General comparison to a product type*.
Example: “German products are usually more reliable, but this one was terrible.”
- Note: Passing mentions of other products/brands without direct comparison do not qualify.

User Role: Now you are given the `review_id`, `prod_name`, and the content of the review. Read the review and output your answer in JSON format without explanation: `{"id": "<review_id>", "category": "<category>"}`. If multiple attributes exist, separate them by a comma. Here is the review: {review content}.

D.3. Dialog Intent Classification and Breakdown Analysis

Dialog Intent Classification and Breakdown Analysis

System Role: You are tasked with labeling conversations between a human and an assistant. Each conversation contains multiple utterances (turns), and you need to label each utterance based on the following criteria:

Criteria 1: Dialog Act Tag. This involves labeling the acts of each utterance in the conversation. The examples provided show why a turn belongs to a specific act tag, but a turn may have more than one tag.

- *Factual Question:* Question, typically posed by the Human, in which the corresponding answer will not be open-ended and neither a simple yes or no. The answer will rarely fluctuate depending on the nature of the human, but rather be a logical response. A sentence can usually be identified as a factual question if it has a correct answer, such as a question asking “How do I do X, Y, and Z”. Most opinion questions are uttered by the Assistant and are located at the very beginning of the conversation.

Example: “Human: I’m willing to try that. How do I reset the modem and router to factory settings?” The last sentence of the utterance is tagged as the Factual Question. Note the use of the word “How”. A factual question differs from an opinion question as the answer to the question will never vary, but rather follow logical steps.

- *Opinion Question:* Question, typically posed by the Assistant, in which the corresponding answer will be open-ended and not a simple yes or no. The answer will often depend on the human, such as the type of technical error a human faces. A sentence can usually be identified as an opinion question if it begins with “How”. Most opinion questions are uttered by the Assistant and are located at the very beginning of the conversation.

Example: “Assistant: Hello! Thank you for contacting Digital Workspace Solutions Inc. My name is Rachel, and I’m here to assist you with troubleshooting any email sending or receiving issues you may be facing. How can I help you today?” The last sentence of the utterance is tagged as the Opinion Question. Note the use of the word “How”.

- *Yes/No Question:* Question, typically posed by both the Assistant and the Human, in which the corresponding answer will be a simple yes or no. A sentence can usually be identified as a Yes/No question if it begins with “Can” or “Have”.

Example: “Human: Hi Emily! I recently purchased a product from your website, but I’m not satisfied with it, and I would like to request a refund. Can you help me with that?” The last sentence of the utterance is tagged as the Yes/No Question. Note the use of the word “Can”.

- *Task Command:* A task command is a statement that prompts the human or assistant to do something. Task commands are similar to the question tags as the task command will also prompt the other individual to respond in a certain manner.

Example: “Assistant: I’m sorry to hear that the software subscription didn’t meet your expectations. Let me clarify our refund policy for you. We offer a 30-day money-back guarantee on our software subscriptions. If you are dissatisfied with the product within 30 days of purchase, you are eligible for a full refund. To initiate the refund process, please provide me with your order details, and I’ll assist you further.” In this utterance, the phrase “please provide me with...” is a task that the assistant is relaying to the human.

- *Invalid Command:* An invalid command occurs when the assistant responds in a way that implies that they failed to solve the human’s problem and are escalating the human’s problem to be solved another way.

Example: “Assistant: I’m sorry to hear that the issue persists. Since the problem extends beyond your local network, there might be an issue with your internet service provider. I’ll escalate the matter to our technical team, and they will investigate further to find a

resolution. Can I have your email address to keep you updated on the progress?” In this utterance, the phrases “escalate the matter to our technical team” and “investigate further to find a resolution” convey that the Assistant failed to effectively solve the Human’s issue. Hence, this utterance will include the Invalid Command tag.

- *Appreciation*: Appreciation is when the human is thanking the assistant for their assistance. Assistant can never have appreciation. Humans can only have appreciation. Appreciation often appears near the end of conversations.

Example: “Human: Thank you, Emily. I’m satisfied with your assistance. Have a great day!” In this utterance, the key words “thank you” and “satisfied” convey that the human is appreciating the assistant’s help. Hence, this utterance will include the appreciation tag.

- *Complaint*: A complaint is when the human details the initial problem that they are facing. The first human utterance in a conversation will almost always contain the complaint.

Example: “Human: Hi John! I recently purchased a hardware device from your company, but it arrived damaged. I would like to understand your refund policy and process for returning the product and getting a refund.” In this utterance, the phrase “it arrived damaged” signals the complaint. This was the first utterance made by the human in the conversation.

- *Comment*: The first sentence in an utterance that addresses a part of the previous utterance. The comment is the direct reply from the Human or Assistant to the previous statement made by either the Assistant or the Human.

Example: “It makes sense now. I’ll wait for the maintenance to be completed and see if the email service starts working normally afterward. Thank you for your help, Rachel!” In this utterance, the sentence “It makes sense now” is the direct reply to the previous utterance, so this will be tagged as the comment.

- *Statement non-opinion*: Statement non-opinions are sentences that directly follow the comment. When these statements are made by the Assistant, they typically show understanding of the problem. Statements can also be made by Human, but these types of statements are vague.

Example: “Human: Thank you for explaining the refund policy. I would like to proceed with the refund. My order number is 12345, and I purchased the subscription three days ago.” In this utterance, the sentence “I would like to proceed with the refund” is a Statement non-opinion because it is directly after the comment and because it is neither a task nor question but rather simply a statement.

- *Positive answer*: A sentence in an utterance that contains a positive connotation when addressing the bug or issue that the human was facing. Humans can only have a positive answer; the assistant will never have a positive answer. The Positive answer will indicate that the Human’s complaint is showing improvement. Identify positive answers by understanding the initial complaint that the human made. Positive answers tend to contain the phrases “now” and “without any issues”.

Example: “Human: I’ve compressed the presentation file as instructed, and now I can send the email with the attachment without any issues. Thank you, Alex!” In this utterance, you can tell that the Human’s complaint is being resolved because the Human correctly followed the Assistant’s guidelines and the Human now “can send the email with the attachment without any issues”. Hence, this is tagged as a Positive answer.

- *Negative answer*: A sentence in an utterance that contains a negative connotation when addressing the bug or issue that the human was facing. Humans can only have a negative answer; the assistant will never have a negative answer. The Negative answer will indicate that the Human’s complaint is still not being resolved. Identify negative answers by understanding the initial complaint that the human made. Negative answers tend to contain the word “still”.

Example: “Human: I followed the steps, and the print queue is cleared. I restarted the print spooler as well, but the printer still won’t print.” In this utterance, the word “still” signals how the complaint still has not been resolved. Hence, the last sentence would be tagged as the negative answer.

Criteria 2: Error Tag. This identifies whether an utterance in the conversation leads to a breakdown. Each utterance is limited to a single classification of error potential.

- *Not a breakdown:* An utterance made by the Assistant or Human is tagged as Not a breakdown if it poses a question or explicitly states a task that will keep the conversation going.

Example: “Human: Hi Emily! I recently purchased a product from your website, but I’m not satisfied with it, and I would like to request a refund. Can you help me with that?” As the Human’s utterance ultimately poses a question, this will be tagged as Not a breakdown.

- *Possible breakdown:* A possible breakdown occurs when there is a notable risk of the conversation stopping. An utterance is a possible breakdown if it does not pose a question that will keep the conversation going.

Example: “Human: Yes, I’m trying to send a relatively large file. It’s a presentation with graphics and videos.” As the Human’s utterance solely includes statements and lacks a question or task command, this will be tagged as Possible breakdown.

- *Breakdown:* A breakdown occurs when the conversation stops. An utterance is a breakdown if it does not continue. This tag occurs at the end of each conversation.

Example: “Assistant: You too! Have a wonderful day, and don’t hesitate to contact us if you need further assistance with your email or any other digital workspace matters. Goodbye!” This is usually the end of each conversation. Hence, this is a breakdown.

User Role: You will be given a conversation consisting of multiple turns. Please label each utterance in the conversation and return the results in the following JSON format: `{"con_id": "<conversation_id>", "turn_id": "<turn_id>", "tag1": "<dialog_intent_tag>", "tag2": "<breakdown_tag>"}`. If multiple dialog act tags exist, separate them by a comma. Here is the conversation: {conversation content}.

D.4. Geographical Information Extraction

Geographical Information Extraction

System Role: Please browse all the information on each product HTML page you get assigned. Based on all the information from top to bottom (including consumer reviews if any), label the following columns:

Section 0:

- Column 1: ASIN
A unique code for each product.

Section 1: Product Description

- First, go through the product description.
Do the sellers explicitly mention the “Country of Origin” in their texts?
Country of Origin is usually stated in Product Description etc., usually following the format: “manufactured in _,” “assembled in _,” “Made in _,” with the blank being the “Country of Origin”.

- Column 2: Manufactured in the US (objective measure)
Put in 1 as an explicit mention of this product being manufactured in the US.
Put in 0 if no information states which country the product was made.

- Column 3: Manufactured Internationally (objective measure)
Put in 1 as an explicit mention of this product being manufactured internationally.
Put in 0 if no information states which country the product was made.

Section 2: Customer Reviews

- Next, see if buyers explicitly mention the “Country of Origin” in their reviews.
- Column 4: Manufactured in the US
Put in 1 as an explicit mention of this product being manufactured in the US in the customer reviews.
Put in 0 if no information states which country the product was made.
- Column 5: Manufactured internationally
Put in 1 as an explicit mention of this product being manufactured internationally in the customer reviews.
Put in 0 if no information states which country the product was made.

Additional Notes:

1. Do not infer the country of origin based on the manufacturing names.
2. It will be rare to have a (1, 1) tagging for (Column 2, Column 3), check again for the information.
3. If a product does not list its manufacturing location, it will translate to (0, 0) in (Column 2, Column 3).
4. Common racist comments do not indicate manufacturing location. For example, “Stupid Chinese” does not explicitly indicate something made in China.
5. Especially for pharmaceutical, food, and beverage products, manufacturing location may be included in the images on the packaging.
6. Do not assume a company manufactures its products in its home country. For example, Sony does not necessarily manufacture all its products in Japan.

Here are some confusing scenarios and what the tag should be:

- For the following situations, put “1” for Explicitly US:
Manufactured in the US, Printed in the US, Manufactured by: “[US Address]”, and “Imported and Made in the US”.
- For the following situations, put “1” for Explicitly International:
Manufactured internationally, “Imported and Made in the US”.
- The following situations do not indicate explicit location of manufacturing by themselves: Shipment and prepayment from US, US-based team is here to help, Small business in the US, Currently, it can be shipped only within the US and to APO/FBO addresses, Federal Approval (e.g., FDA approval), Labeled to the US Standards, Manufactured for US, Energy Star US Approved, American Manufacturer/Business, Vague generalizations (e.g., “The Chinese make bad products!”), and Tangential actions (“tested,” “engineered,” “verified,” etc., in the USA).

User Role: Now you are given the HTML file. Read through the file and output your answer in JSON format without explanation: {"ASIN": "<ASIN>", "Manufactured_US_seller": "<col2>", "Manufactured_Intl_seller": "<col3>", "Manufactured_US_customer": "<col4>", "Manufactured_Intl_customer": "<col5>"} Here are the texts from one HTML file: {product webpage texts}.

D.5. Language Toxicity Detection

Language Toxicity Detection

System Role: Please classify social media posts into one of the following categories based on their content: ‘fearspeech’, ‘hatespeech’, ‘fearspeech, hatespeech’, ‘normal’, and ‘confused’ for cases where the classification is unclear. Further, you also need to mark the target communities toward which the particular posts are targeted. This classification should be based on the content’s intent and the targeted community, without providing any explanatory text. Your response should strictly follow this format: “[Label] ### [Target Group]”. The label will be one of the specified categories based on the content’s nature, and the target group should be identified based on who the post is directed at. The target group should be mentioned even if the label is ‘normal’ or ‘confused’, using ‘other’ for posts not targeting any specific group or ‘unclear’ if the target group cannot be determined.

Hate speech is a language used to express hatred toward a targeted individual or group or is intended to be derogatory to humiliate or to insult the members of the group on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender. A post is a hate speech if one or more of the following are true:

- It is targeted against a person or group of persons.
- It uses derogatory or racial slur words within the post.
- It makes use of disparaging terms with the intent to harm or incite harm.
- It refers to and supports other hateful facts, hate posts, and organization.
- It refers to the other group as inferior as cultural superiority.
- It makes use of idiomatic metaphorical collocation or any other indirect means of expressions that are harmful or may incite harm.
- It expresses violent communications.

Fear speech is an expression aimed at instilling (existential) fear of a target group on the basis of attributes such as race, religion, ethnic origin, sexual orientation, disability, or gender. A post is a fear speech if it creates fear about a target group using one of the following notions:

- Something done by the target group in the past (and the possibility of that happening again) - historical domination.
- Some tradition of the target group which is shown to take precedence over in-groups - cultural domination.
- The target group taking over jobs or education institutes economic domination.
- The target group taking over land/ living places - geographic domination.
- The target group killing people of the in-group - existential domination.
- Speculation that the target group would take over and dominate in the future over the in group - future domination.

Normal speech is the label of the posts which are neither hate speech nor fear speech. Note that this class is not equivalent to unbiased or polite language.

Specific guidelines:

- The presence of certain words (e.g., use of slur word, political propaganda) does not justify a text being hateful or fearful. The annotators should look into the context of the post.
- Since some of the fear speech heavily used common news sources, please look into the post if it is a news headline or if it is trying to create or spread fear.
- A post might be both partially hateful and partially fearful. Please carefully read the whole post before finalising the labels.
- Fear and hate speech both should be about some target community (explicit or implicit). Fear/hate speech about media or government institutions are not considered in this task. Such cases should be marked as normal.

Some of the annotated examples are shown below:

- “I call bullshit on Google. How does a search for ‘white parents with white children’ return these images?” [normal ### other]
- “Thousands of Americans have been killed by illegal aliens. Illegals break up American families forever. Go home. Stay home. Stop breeding out of control.” [fearspeech, hate-speech ### refugee]
- “Toledo Tree-Dweller Guns Down White Man After an Argument at a Bar. Blacks routinely use homicide as their go-to for conflict resolution.” [fearspeech ### African]
- “Today, do something for the environment and kill your local queer.” [hatespeech ### homosexual]

User Role: Given the following post, label it as '**fearspeech**', '**hatespeech**', '**fearspeech**, **hatespeech**', '**normal**', or '**confused**'.

Please return the results in the following JSON format without explanation: {"id": "<id>", "label": "<label>"}.

D.6. Criticism Stance Detection

Criticism Stance Detection

System Role: You are a social media analysis expert with a keen understanding of how scientific discourse unfolds online, and your task is to distinguish tweets that express doubt or critique towards research findings.

Project Overview:

Retraction in the scientific literature, whether because of research fraud or mistake, undermines science and the public trust in scientific knowledge. However, it is a challenge to spot low-quality papers, as they basically fooled the peer-review system that science relies on to legitimize new findings through expert evaluation. A promising approach is to identify them after publication—the sooner we can discover them, the less damage they will cause.

This project studies whether social media attention can help us identify retracted papers.

- First, we want to understand whether retracted papers attract more attention before being retracted than normal papers do.
- Second, we examine whether social media posts (Tweets in particular) express skepticism about these papers that can be helpful for retraction detection.
- Third, we investigate which platform’s attention and content are more likely to correlate with retraction. Understanding these questions is the first step towards building automated tools to help retraction detection.

Task Overview:

We collected pre-retraction tweets related to thousands of retracted papers and non-retracted papers. Each tweet discusses something about a paper (with a URL to its DOI). We want to pick out tweets that question the paper’s findings.

For example:

1. Are Moral Evaluations Faster, More Extreme, Than Pragmatic Evaluations?
<http://t.co/DstRWjq7RT>
2. The importance of stupidity in scientific research: <http://t.co/DAhof3Jh>

Our definition of uncertainty is: *A tweet about personal opinions expressing feelings of uncertainty, such as doubt, skepticism, criticism, concern, confusion, disbelief to a paper’s author, data, finding, credibility, novelty, contribution, or other scientific elements.*

There are three columns in the file: (**tid**, **text**, **is_uncertain**). The first two columns are tweet ID and tweet text; the third column is where you need to label each tweet as whether it expresses uncertainty (**assign \1**) or not (**assign \0**). Note that an “unsure” response is not allowed: you have to give a judgement with your own interpretation in those cases.

Examples and Edge Cases:

1. How is it possible that this study hasn't been retracted? Orac? Skeptical Rapture? Get on it! <https://t.co/Jedss1qa8D>
Label: 1
Note: Negative opinion.
2. LOL WHO DID THIS RESEARCH. YALL KNOW HYPERTENSION CAN BE PASSED DOWN YALL REAL LIFE DUMB <https://t.co/aPvbEWJKdz>
Label: 1
Note: Negative opinion.
3. Bet the vaccine fanatics are trying to get this paper retracted. <https://t.co/SEJ97WnqKO>
Label: 1
Note: Includes the word "retracted."
4. 3D printing in science <http://t.co/Gbeqkequ5g>
Label: 0
Note: Advertisement.
5. This study shows how injected #aluminum causes alterations of chemicals in animals that is consistent with #autism <https://t.co/vdxl0p21c0>
Label: 0
Note: Reports findings.

Labeling Tips:

- Many tweets are talking about non-retracted papers.
- You shouldn't label them based on whether the paper is retracted or not. In other words, tweets about retracted papers could be labeled as "0," and tweets about non-retracted papers could be labeled as "1."
- Tweets describing findings without personal opinions or reactions can be labeled quickly as 0.
- Tweets mentioning @RetractionWatch or containing the word "retracted" are strong signals for uncertainty.
- Tweets about retraction announcements should **not** be labeled as "1." For example:
 - The study of Hofmann et al. 2015 (<https://t.co/oBYxKfdtFZ>) is going to be retracted due to coding errors identified by @wdonald_1985 and me.
 - RETRACTED: The impact of medically supervised injection centres on drug-related harms: a meta-analysis <https://t.co/gTA69isRLp>.

User Role: Now you are given the `tid` and the content of the tweet. Read the tweet and output your answer in JSON format without explanation: `{"id": "<id>", "label": "<is_uncertain>"}`. Here is the tweet: {tweet content}.

D.7. Sentiment Analysis**Sentiment Analysis**

System Role: Please identify the sentiment of the review as 'positive', 'negative', or 'confused', without any additional explanation.

User Role: Label the sentiment of this post: {post content}.